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Investor Sentiment and Volatility Timing: Evidence from European Markets

Analysis of Quantitative Investment Strategy

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Abstract

The purpose of this study is to analyze the performance and dynamics of several investment strategies. The individual part focuses on exploring the profitability of a cross-sectional long-only trading strategy that explores return differences between sentiment-prone and sentiment-insensitive stocks, using the VSTOXX as a sentiment indicator for the European stock market. The strategy consists of holding sentiment-prone stocks when the sentiment is good and sentiment-insensitive stocks when sentiment is bad. In the group part, several strategies were combined to form three portfolios: Equal-Weighted, Tangency and Global Minimum Variance. The group report is presented first, followed by the individual contribution.

Keywords: Financial Markets, Quantitative Investment Strategy, Investor Sentiment, Volatility Timing, European Stock Market, Portfolio Optimization.

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1 Introduction

The ongoing pursuit to create the optimal portfolio has led to extensive academic research on portfolio optimization. Markowitz (1952) highlighted the delicate balance between expected returns' attractiveness and associated risks, suggesting that a combination of multiple securities with imperfect correlations can significantly reduce portfolio risk and enhance the risk-reward equilibrium. In today's landscape, sophisticated algorithmic programs delve into financial data as part of quantitative investment strategies, encompassing statistical arbitrage, machine learning techniques, and artificial intelligence approaches. These methodologies aim to identify signals indicating that a stock is likely to outperform the market. As the competition between traditional and quantitative investment methods intensifies, hedge funds and investors are on a quest to discover novel approaches that yield abnormal returns.

This project combines five individual quantitative investment strategies: the Volatility Timing & Momentum in U.K. Stock Market, Exploiting Value Premium in U.S. Stock Market, Efficiency & Growth in U.S. Stock Market, Investor Sentiment and Volatility Timing in European Stock Market and Carry & Momentum in FX Market. Further details on these strategies are provided in the upcoming section. The individual strategies were combined into three different portfolios: the equal weighted portfolio, the tangency portfolio, and the global minimum variance portfolio. The objective of this analysis is to assess the extent to which these diversified portfolios outperform the individual strategies in isolation. This involves analyzing whether each portfolio offers investors superior risk-adjusted returns. The overarching goal is to construct portfolios that combine various assets through allocation, minimizing risk, and optimizing returns. The analysis unfolds as follows: Section 2 offers a brief description of the individual strategies, including their construction and performance metrics. Section 3 delves into the comparison of the individual strategies, followed by subsection 3.3, which details how the individual portfolios are combined to form the Equal-Weight, Tangency and GMV portfolios. Subsequent sections explore the naive performance of these combined portfolios and present regression analysis using the Fama French 3-Factor Model and Fama French 5-Factor Model. Finally, the last subsection 3.6, evaluates the performance of the Diversified Tangency and Global Minimum Variance Portfolios, which includes two additional asset classes to the previous investment strategies, in order to assess the effectiveness of this diversification to provide investors with higher risk-adjusted returns.

2 Individual Strategies

2.1 Strategy 1: Investor Sentiment and Volatility Timing

2.1.1 Economic Motivation

Investor sentiment has been defined by Baker and Wurgler (2007) as ”a belief about future cash flows and investment risks that is not justified by the facts at hand” that deviates asset’s valuation from their intrisic value. Over the last two decades, several measures and indexes of investor sentiment have been developed, like the VIX, the VSTOXX and the Consumer Confidence Index, and investment strategies that exploit the informational value of these measures, together with technological advances, are on the rise.

Sentiment is a good predictor of stock returns, with particularly significant predictive power for the short and medium-term (see Schmeling, 2009). When using high-frequency indicators, the relation between sentiment and stock returns is positive in the short-term (Han and Li, 2017), pointing towards a momentary effect that drives prices further away from the fundamental, leading to prolonged mispricing.

Taking the aforementioned into consideration, this dissertation evaluates the hypothesis that the expected volatility (proxied by the VSTOXX) is a good indicator of European market sentiment, with high VSTOXX indicating low market sentiment and low VSTOXX indicating high market sentiment, and thus can predict performance differences between sentiment-sensitive and sentiment-insensitive stocks.

To test this hypothesis, I create portfolios of sentiment-prone stocks and sentiment-insensitive stocks, and implement a long-only strategy that selectively goes long either the sentiment-prone portfolio (when sentiment is good) or the sentiment-insensitive portfolio (when sentiment is poor). The choice is based on the sentiment indicated by the VSTOXX.

2.1.2 Data and Methodology

The analysis is carried out for the European stock market, proxied by 11 of its biggest economies: Germany, United Kingdom, France, Italy, Spain, Netherlands, Switzerland, Poland, Sweden, Belgium, and Russia. The sample period ranges from January 1999 to September 2023 and comprises, initially, 10761 firms.

To start, I calculate the value of firm characteristics connected to the firm's exposure to arbitrage constraints and, consequently, to market sentiment. Following Ding et al. (2021), the computed firm-level characteristics are: firm size (ME), Age, return volatility (σ_r), earnings ratio (E/BE), dividend ratio (DIV/BE), tangible and intangible asset ratio (PP&E/A and R&D/A), book-to-market ratio (BE/ME), external finance ratio (EF/A) and Sales Growth. To compute these characteristics, annual firm-level accounting data was downloaded from the Compustat database from June 1997 to September 2023. To ensure the reliability of the data, duplicates were removed. The data was then resampled from annual to monthly frequency, since return data is monthly.

Monthly stock returns for the sample period are computed using daily price information extracted from Compustat. For each company, only the observations regarding their primary issue are kept. Moreover, to avoid data errors, firms with at least a price equal to zero are removed. Compustat only provides daily closing prices, so, following Jensen et al. (2023), stock split and dividend adjusted prices for firm *i* at time *t* are computed as:

$$PRCAdj_{i,t} = \frac{PRCCD_{i,t}}{AJEXDI_{i,t}} \times TRFD_{i,t} \tag{1}$$

where $PRCCD$ is the closing price for firm i at time t, $AJEXDI$ is the cumulative split adjustment factor for firm i at time t, and $TRFD$ is the daily total return factor of firm i at time t to account for cash-equivalent distributions, like dividends. To obtain monthly returns, only month-end adjusted price observations are kept. Then, returns are computed and converted to US Dollars

(Jensen et al., 2023) according to the formula:

$$Ret_{i,t} = \left(\frac{PRCAdj_{i,t}}{PRCAdj_{i,t-1}} - 1 \right) \times FX_{i,t} \tag{2}$$

where $Ret_{i,t}$ is the return for firm i at time t, and FXi, t is the exchange rate for firm i stock's quote currency at time t. Monthly exchange rate data was obtained from the FRED website. To transform these into excess returns, the risk-free rate data has been retrieved from Kenneth French Data Library. Before building the strategies, the year-end accounting data of year *t-1* is matched to monthly returns from July *t* to June *t+1*, to avoid forward-looking bias. Moreover, daily VSTOXX data for the sample period is retrieved from Qontigo's website.

For each day, sentiment is defined as bad if the VSTOXX is at least 10% higher than the average of the prior 25-day historical level, and sentiment is good otherwise.

With all the data prepared, equal-weighted decile portfolios are built for each firm characteristic. Then, the decile portfolios are classified as prone and insensitive for each characteristic, resulting in 16 different combinations. Afterwards, the "Long VSTOXX" (LVSTOXX) strategy is created, by going long the sentiment-prone decile portfolio if sentiment is good (low VSTOXX) and going long the sentiment-insensitive decile portfolio if sentiment is bad (high VSTOXX). This strategy was then applied to each of the 16 combinations of prone and insensitive decile portfolios. To assess the relative performance of the LVSTOXX strategy, the European Market factor from the Kenneth French library is used as a benchmark, and the "Excess Long VSTOXX" (ELVSTOXX) strategy was built, by subtracting the benchmark returns from the LVSTOXX strategy returns each month. Finally, an equal-weighted Aggregate portfolio of all the LVSTOXX portfolios was computed, to assess the overall performance of the sentiment strategy.

To assess the performance of the portfolios, a naïve performance analysis using: average excess return, standard deviation and Sharpe Ratio, all annualized, is performed. Then, to measure factor exposure and abnormal returns, I regressed the LVSTOXX returns on the Fama-French European 3 Factors and the European Momentum Factor (FF3 + Mom). The data for the factor analysis was retrieved from Kenneth French Data Library. Finally, a sub-sample performance analysis of the strategy is perfomed during the Subprime Crisis (January 2008 to March 2009) and the

Covid/Ukrainian War Crisis (September 2020 to June 2023).

2.1.3 Performance Analysis

First, strategy results are naïvely analysed, considering the average annualized excess returns (ARet), annualized volatility (Vol), the skewness (Skew), and the Sharpe Ratio (SR). Below, Table 1 summarizes the performance of the LVSTOXX strategy (Panel A) and the excess returns of the LVSTOXX over the market benchmark (Panel B). The success column represents the fraction of days in which Excess LVSTOXX is zero or higher.

Table 1: *Summary Statistics for the Long-Only VSTOXX Trading Strategy*

Factor	Panel A. LVSTOXX				Panel B. Excess LVSTOXX				
	ARet	Vol	Skew	SR	ARet	Vol	Skew	SR	Success
E/BE	10.15	19.16	-0.43	0.53	4.36	11.87	0.08	0.37	*0.52*
PP&E/A	13.05	23.18	0.61	0.56	7.11	19.54	1.18	0.36	*0.53*
R&D/A	10.66	19.42	-0.70	0.55	4.84	12.79	0.17	0.38	*0.53*
EF/A_1	9.43	19.46	-0.68	0.48	3.67	14.11	0.15	0.26	*0.52*
EF/A_2	4.56	20.64	0.20	0.22	-0.96	16.07	0.71	-0.06	*0.47*
EF/A_3	11.28	17.93	-0.40	0.63	5.43	13.35	0.19	0.41	*0.54*
DIV/BE	13.6	20.25	-0.32	0.67	7.64	12.28	0.23	0.62	*0.56*
Age	5.38	20.66	0.23	0.26	-0.19	16.88	0.67	-0.01	*0.46*
ME	12.79	19.68	-0.22	0.65	6.86	16.94	0.56	0.40	*0.56*
BE/ME_1	0.26	11.10	-2.13	0.02	-5.05	13.42	0.05	-0.38	*0.44*
BE/ME_2	10.53	19.47	-0.85	0.54	4.71	11.55	0.09	0.41	*0.53*
BE/ME_3	-1.61	12.32	-2.66	-0.13	-6.83	13.54	0.11	-0.50	*0.41*
σ_r	15.32	26.82	0.65	0.57	9.27	23.55	0.84	0.39	*0.54*
Sales $Growth_1$	11.03	20.23	-0.38	0.55	5.19	14.88	0.08	0.35	*0.52*
Sales $Growth_2$	6.25	18.94	-0.17	0.33	0.65	14.60	0.35	0.04	*0.48*
Sales $Growth_3$	13.31	19.04	-0.18	0.70	7.36	14.52	0.11	0.51	*0.54*
EW Aggregate	9.03	17.55	-0.31	0.51	3.29	12.82	0.33	0.26	*0.49*

Looking into Panel A, one can see that, overall, the LVSTOXX trading strategy is able to generate positive returns for the vast majority of portfolios, with the annualized returns ranging from 15.32% (σ_r portfolio) to -1.61% (BE/ME_3 portfolio). Looking into the risk-adjusted returns, measured by the Sharpe ratio, the values are fairly satisfactory, ranging from 0.7 (Sales $Growth_3$ portfolio) to -0.13 (BE/ME_3 portfolio). Looking into Panel B, it is clear that the LVSTOXX strategy is able to outperform the benchmark market portfolio (with four exceptions), as shown by the positive and nontrivial excess returns, which range from 9.27% (σ_r portfolio) to -6.83% (BE/ME$_3$ portfolio), yielded by the Excess LVSTOXX strategy. Moreover, the average success of the Excess LVSTOXX strategy is 51%, meaning that the strategy generates higher returns than the benchmark in half of the months.

Equal-weighting all the sentiment portfolios, creating the an Aggregate portfolio, the overall result of trading based on sentiment is a profitable strategy, as shown by the last row of the Table 1. This aggregate strategy generates a 9.03% excess return and a 0.51 Sharpe ratio when evaluated as a stand-alone strategy, and yields a 3.29% return and 0.26 Sharpe ratio when the benchmark portfolio returns are deducted. The skewness is close to zero in both the cases, meaning that the strategy has small tail risk and low probability of extreme returns. Overall, this strategy is able to outperform the benchmark in 49% of the months.

The naïve analysis omits the underlying risk factors that drive the returns, so the excess returns were adjusted using the CAPM and the FF3 + Momentum models. The results for the alpha and Market of the aggregate portfolio are summarized below, on Table 2 .

Table 2: *LVSTOXX abnormal alphas for the CAPM e FF3 + Momentum Regressions*

Factor	Panel A. CAPM					Panel B. FF3 + Momentum				
	Alpha	*(t-stat)*	β_{Mkt}	*(t-stat)*	R^2	Alpha	*(t-stat)*	β_{Mkt}	*(t-stat)*	R^2
EW Aggregate	4.94	*(2.17)*	0.69	*(19.10)*	0.55	6.35	*(3.23)*	0.63	*(19.20)*	0.70

The results are, in general, consistent between the two models, and the portfolio presents an alpha that is smaller than the excess returns from the LVSTOXX strategy, suggesting that the good performance of the strategy is partly driven by additional risk. Moreover, the overall high R^2's, and statistically significant coefficients of risk factors associated with both models indicates the strategy is closely associated with the risk factors.

The Aggregate EW portfolio generates high (4.94% for the CAPM and 6.35% for the FF3 + Mom) and statistically significant alphas. A high R^2 (0.70) reinforces the evidence of profitability. The positive and statistically exposure to the market factor shows great exposure to market fluctuations and incapacity to provide some hedge against drawdowns.

Due to sentiment's weak predictive power during recessions, a cumulative return and subsample analysis during bear market periods (the Subprime and the Covid/Ukranian War Crisis) is performed. The analysis is performed for the LVSTOXX strategy, using the Age, Sales Growth$_3$, BE/ME$_1$ portfolios, and EW Aggregate portfolio, since these represent different characteristics and allow for a comprehensive analysis of the full range of portfolios.

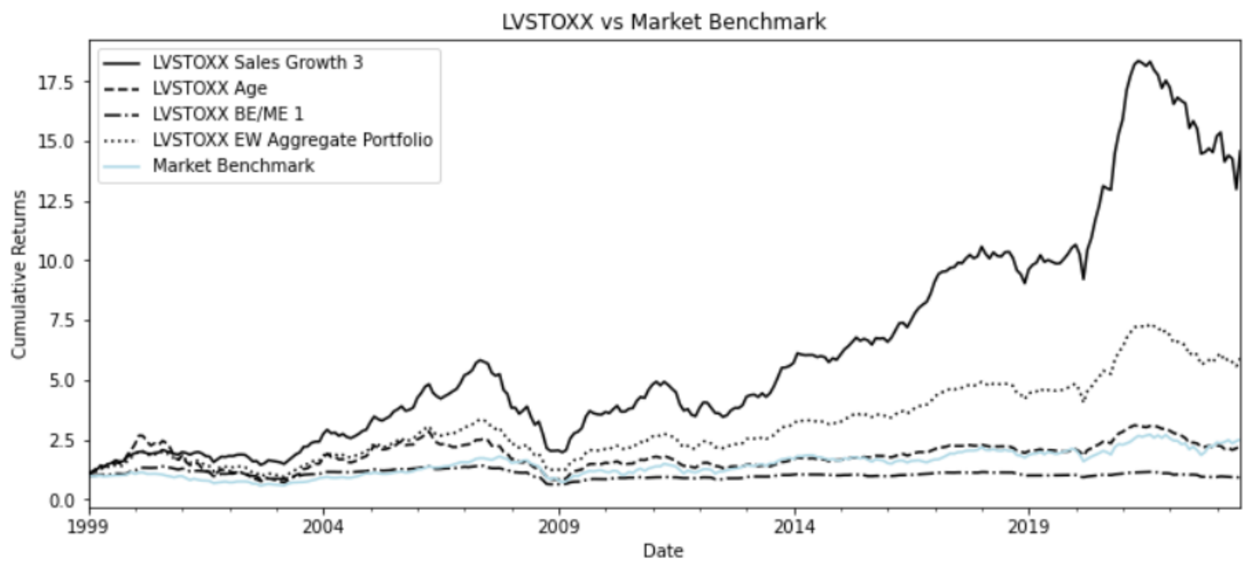

Figure 1: *Cumulative returns of LVSTOXX strategies against the market portfolio*

From Figure 1, it becomes clear that the performance of the LVSTOXX strategy is highly dependent on market conditions, due to how closely the strategies cumulative returns follow the market trend, evidencing high correlation, with the portfolios depicted suffering major drawdowns during recessions, providing no hedge against extreme events.

The differences in the magnitude of variation of cumulative returns are suggestive of possible capacity of the sentiment strategies to outperform the benchmark during distress periods, despite the overall poor performance. Looking into Table 3, it is noticeable how the LVSTOXX strategy outperforms the market benchmark during the Subprime crisis, with an Aggregate excess return of 3.8%. However, this is not the case for the Covid and Ukrainian War crisis, during which the sentiment portfolios under-perform the benchmark. The fact that there was a period of bullish market during the Covid crisis, along with seemingly contradictory lower success rates and higher returns during the Subprime, suggest that the strategy is able to protect against down-side risk during prolonged recessions, but has poor predictive power during regime-switching periods.

Table 3: *Summary Statistics for the Excess LVSTOXX strategy during recessions*

Factor	Panel A. Subprime				Panel B. Covid/Ukranian War			
	ARet	Volatility	SR	Success	ARet	Volatility	SR	Success
BE/ME_1	9.80	19.25	0.51	*0.47*	-11.25	16.79	-0.67	*0.44*
Age	3.80	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*
Sales $Growth_3$	2.10	19.09	0.11	*0.33*	-7.63	15.90	-0.48	*0.50*
EW Aggregate	3.80	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*

The EW Aggregate strategy is used for the construction of the combined portfolios, since it gives the broadest view on the performance of the sentiment strategies studied.

2.2 Efficiency and Growth: An Integrated Analysis of Portfolio Optimization via a Multi-factor Model in the North American Stock Market

2.2.1 Economic Motivation

The pursuit of the optimal portfolio, a perpetual challenge for investors, has been shaped by seminal contributions. Harry Markowitz's 1952 work emphasized diversification to balance expected returns and risks (Markowitz, 1952, 77–91). William Sharpe's CAPM introduced a market portfolio approach, contingent on market efficiency (Sharpe, 1964, 425-442). Challenges to CAPM led to Fama and French's influential three-factor model in 1992, expanded to a five-factor model in 2015 (Fama and French, 2015, 1-22).

While factors like volatility (Haugen and Baker, 1991, 39 f.), dividend yield (Blume, 1980, 577), and earnings quality (Sloan, 1996, 314) gained prominence, the subjective nature of quality metrics became apparent (Sloan, 1996, 27). This study aims to integrate these findings, specifically focusing on the concepts of efficiency and growth, to construct an optimal portfolio. The strategy is predicated upon the construction of a score for each portfolio. Drawing inspiration from Mohanram

(2005), Asness et al. (2019), and Kurniawan (2021), this score is built upon three key financial metrics. For this purpose, individual scores are ascertained for distinct factors. The selection of these factors is grounded in specific economic rationales:

- Asset Turnover: Measures the efficiency of a firm in generating revenue from its assets (Kurniawan, 2021, 64-72).
- ROA: Evaluates the company's capability to transform its investments into profits (Asness et al., 2019, 43 ff.).
- Sales Growth (12 months): Indicates a company's growing market reach and diversifying revenue channels.

In order to assign equal significance to each metric and streamline their combination, the standardized z-score method, as introduced by Asness et al. (2019) in their study (Asness et al., 2019, p. 43), is employed. Specifically, on a monthly basis:

1. Variables are transformed into ranks.
2. The ranks are standardized to derive a z-score.

This research employs two methodologies to determine optimal weights for crucial financial factors, culminating in a hybrid investment strategy. The Total Z-score Approach assigns equal importance to all factors, yielding a cumulative z-score by summing individual z-scores for Asset Turnover, ROA, and Growth. This identifies stocks with a high cumulative z-score, indicating superior performance.

The Mean Variance Weights Approach, rooted in Harry Markowitz's Modern Portfolio Theory, maximizes return relative to standard deviation. The focus is on the tangency portfolio, but determining optimal weights for individual securities is challenging. This study addresses this by employing factor portfolios based on Asset Turnover, ROA, and Growth. Monthly portfolios are constructed, ranked, and leveraged to optimize mean variance weights, enhancing the Sharpe ratio.

The final strategy combines both approaches, acknowledging the limitations of mean variance weights over time. The total return is an average of equal-weighted Total Z-score and mean variance approaches, ensuring adaptability to diverse market conditions. This balanced methodology aims for optimal performance by considering distinctive financial factors' attributes.

2.2.2 Data and Methodology

The data under study originates from three distinct sources. The first dataset was extracted from Compustat, providing a comprehensive view of financial and accounting metrics for all North American companies, encompassing the required datapoints available in the database. The second dataset encompasses stock return data and shares outstanding for each stock across varying fiscal dates, obtained in US Dollars from CRSP. Additionally, the S&P 500 index dataset, serving as a benchmark, is also acquired from CRSP. To calculate refined metrics like the Sharpe ratio and excess returns, the risk-free return was sourced from the Fama and Kenneth database. Additionally, both the market excess return (used as a benchmark) and the FF5 factor portfolios were also sourced from the Fama and Kenneth database.

The endeavor of fusing data from disparate databases, each with its intrinsic set of identifiers, posed challenges. A salient distinction between the databases is their choice of stock identifiers. While CRSP uses the PERMNO as a stock identifier, Compustat utilizes the Global Company Key. Although direct data merger on common attributes like ticker symbols was feasible, the process demanded rigorous attention to detail to ensure the fidelity of the resultant dataset. To ensure pristine data integrity, any duplicate entries were systematically eliminated from the dataset. Financial datasets, by their very nature, often present researchers with the challenge of sporadic missing values.

A further point to consider was the inherent limitation of Compustat data being available only on a quarterly basis. To bridge potential data voids, especially post-resampling, a forward-filling technique was employed. This strategy, extending up to a 12-month window, was pivotal in interpolating gaps between quarters and addressing any missing data. This approach is in line with

Fama and French's portfolio formation framework. Therefore quarterly accounting/ fundamental variables are held constant throughout the quarters.

Once the relevant data from CRSP and Compustat had been merged together, the next step involved calculating key financial ratios. The metrics such as Operating Income Before Depreciation, Revenue, and Total Assets were used to determine the Return on Assets (ROA) and Asset Turnover. Furthermore, revenue data was instrumental in computing the quarterly revenue growth. The market value of each stock was calculated by multiplying the closing price, sourced from campustat, with the number of outstanding shares, acquired from CRSP. This method is crucial for value weighting.

In analyzing performance, returns were adjusted to account for a time lag. This adjustment reflects a cautious approach, considering that new accounting or fundamental data might not be immediately available when portfolios are formed. This ensures a sequential order: the analysis is carried out first, then the investment decision is made, and finally, the resulting returns from that investment are observed. This lagging approach guarantees that the returns are a consequence of the preceding analysis and investment, and not the other way around.

2.2.3 Performance Analysis

The 'Long Top' portfolio markedly outperforms the 'Long Bottom' strategy with an average annual return of 18.53% and a Sharpe Ratio of 0.97, suggesting a successful identification and investment in high-performing stocks. The 'Long Bottom' strategy, conversely, indicates a selection of underperforming assets, offering an average annual return of 3.86% and a Sharpe Ratio of 0.18.

The S&P 500 and Market portfolios, used as benchmarks, show average annual returns of 2.78% and 5.73%, respectively. The Long-Short portfolio stands out by achieving a 12.06% average annual return with an annualized volatility comparable to the benchmarks (16.71% vs. 15.48% and 16.00% for the S&P 500 and Market, respectively).

This strategy yields a higher reward-to-risk ratio, evidenced by its Sharpe Ratio of 0.72, compared to 0.18 for the S&P and 0.36 for the Market. The Long-Short portfolio consistently surpasses the S&P 500 and Market benchmarks across the sample period. Detailed performance metrics are available below in Table 4.

Table 4: *Summary of Performance Statistics Across Different Samples*

			Full Sample				
Index	*AnnualizedReturn*	*AnnualizedVol*	*Skewness*	*Kurtosis*	*SharpeRatio*	*MaxDrawdown*	*PositiveMonths*(%)
Long Top	0.19	0.19	−0.27	1.28	0.97	−0.51	62.44
Long Bottom	0.04	0.21	−0.20	2.92	0.18	−0.70	57.17
Long-Short	0.12	0.17	0.24	1.67	0.72	−0.49	59.80
S&P500	0.03	0.15	−0.45	1.66	0.18	−0.62	56.84
Mkt	0.06	0.16	−0.51	1.78	0.36	−0.54	59.64
			In-Sample				
Index	*AnnualizedReturn*	*AnnualizedVol*	*Skewness*	*Kurtosis*	*SharpeRatio*	*MaxDrawdown*	*PositiveMonths*(%)
Long Top	0.18	0.20	−0.46	1.77	0.90	−0.55	59.93
Long Bottom	0.02	0.19	−0.25	3.53	0.09	−0.57	54.72
Long-Short	0.15	0.16	0.27	0.89	0.99	−0.43	61.89
S&P500	0.02	0.15	−0.34	2.56	0.12	−0.59	53.42
Mkt	0.06	0.16	−0.44	2.77	0.35	−0.53	57.00
			Out-of-Sample				
Index	*AnnualizedReturn*	*AnnualizedVol*	*Skewness*	*Kurtosis*	*SharpeRatio*	*MaxDrawdown*	*PositiveMonths*(%)
Long Top	0.18	0.19	−0.31	1.42	0.96	−0.52	65.99
Long Bottom	0.05	0.24	−0.19	2.00	0.20	−0.71	58.25
Long-Short	0.09	0.18	0.25	1.82	0.52	−0.32	59.26
S&P500	0.03	0.16	−0.55	0.86	0.22	−0.62	59.93
Mkt	0.05	0.16	−0.57	0.89	0.34	−0.54	61.95

The Long-Short strategy stands out for its comparatively lower risk, regarding the maximum drawdown of -48.90% and a positive Skewness of 0.24. This contrasts with alternative strategies that exhibit negative skewnesses and higher drawdowns. In comparison, the S&P 500 and Market portfolios are both negatively skewed with -0.45 and -0.51 offering lower returns and presenting a less stable risk profile than the Long-Short Strategy. In essence, when pitted against the S&P 500 and Market portfolios, it becomes evident that the Long-Short strategy offers superior returns and a more robust risk profile.

However, a more nuanced picture emerges when different time periods are considered separately. During the In-Sample period, the long-short strategy actually outperformed the long-only strategy in terms of the Sharpe ratio (0.99 vs 0.90). This was achieved by adjusting the weights of the factor portfolios through mean-variance analysis, optimizing them to maximize the Sharpe ratio and hence, the risk-adjusted returns. But the scenario changed in the Out-of-Sample period, where the stock market conditions evolved, rendering the previously optimized weights suboptimal. Consequently, the Sharpe ratio for the long-short strategy diminished to 0.52, in contrast to the long-only strategy, which stood at 0.96.

Considering the full sample period, the 'Long Top' strategy outshone the Long-Short strategy in terms of Sharpe ratio and return. This suggests a need for more frequent adjustments to the weights to attain a higher Sharpe ratio, or investors must heighten their awareness of the nuances of such strategies to prevent the erosion of outperformance over time.

As investors increasingly recognize the potential of strategies combining long positions with growth and efficiency, they adapt their approaches accordingly. This heightened awareness and adaptation may contribute to the fading of initially observed superior risk-adjusted returns, highlighting the dynamic and ever-changing nature of investment strategy effectiveness.

The correlation matrix of portfolio returns unveils the 'Long-Short' strategy's remarkable independence from broader market trends. With negligible correlations of 0.005 with the S&P 500 and 0.007 with the market index, the 'Long-Short' portfolio demonstrates a strategic advantage in providing protection during market turbulence. This low correlation suggests a potential shield against drawdowns that may affect traditionally correlated assets.

Moving on to the FF5 regression results, the analysis aligns with the earlier observation of the 'Long-Short' portfolio having a modest market beta (0.030), indicating a minimal relationship with market trends and a favorable characteristic for mitigating market risk. Noteworthy is the substantial Beta for RMW at 0.279, signifying heightened exposure to profitability. However, it's crucial to highlight that T-statistics reveal none of these values as statistically significant at the 5% level, and R-squared values indicate a relatively low explanatory power of the model for these portfolios. The high R-squared values for the S&P 500 and Market portfolios confirm the FF5 model's substantial explanatory power over these benchmark returns (for more details, refer to the individual report).

2.3 Carry & Momentum in FX Market

2.3.1 Economic Motivation

Investors often focus their investment on developed markets, particularly in the most popular currency pairs (USD/GBP, USD/EUR and USD/JPY), which account for 60% of all forex trading volume, according to the 2022 BIS report (<<OTC Foreign Exchange Turnover in April 2022>>). This preference is due to their more liquid foreign exchange markets and stable exchange rate regimes. Considering this, the purpose of the project is to evaluate whether an addition of currencies from emerging market currencies to a portfolio of purely currencies from developed markets leads to a higher value. It was demonstrated by Burnside et al. (2007) that adding emerging market currencies to a portfolio can cause the carry trade's Sharpe ratio to rise dramatically due to its diversification advantages. Also, the study by Menkhoff et al. (2012) found that momentum returns in developed markets are lower than in emerging markets, suggesting that the profitability of momentum strategies relies on the inclusion of smaller, less liquid currencies. This happens because investing in emerging economies can result in greater diversity and better returns because of their greater volatility, development potential, and low correlation with developed markets. To achieve this, two common investment techniques are used to assess the profitability of FX markets: carry trade and momentum.

2.3.2 Data and Methodology

To construct the strategy, data was retrieved using the Refinitiv database to obtain daily spot and one-month forward exchange rates for a sample of 24 currencies, which include 12 emerging market currencies and 12 developed market currencies. All currency strategies are from the viewpoint of a US investor. The strategy covers the sample period from January 1999 to December 2022, transforming daily data into non-overlapping monthly observations. The components of the three-factor model (Fama-French three-factor model (FF3F))from Kenneth French Data Library were used to analyze the performance of the strategies and to run the risk factor model that is commonly used to explain stock returns (FF3F).

The carry (C_t) for each currency is calculated using the formula below:

$$C_t = \frac{S_t - F_t}{F_t} \tag{3}$$

Equation 3: carry of a fully collateralized position, where S_t is the spot rate and F_t is the forward rate

The carry trade was performed by sorting all currencies in terciles, in ascending order according to their carry (using equation 3). For the momentum strategy, currencies were sorted in terciles, in ascending order at the end of each month, based on the lagged returns during the previous 3, 6, 9, and 12 months, using a 1-month holding period. For both techniques, the portfolios are equal weighted and rebalanced at the end of each month. In the carry trade, it takes a long position in the portfolio of currencies with higher carry (P_3) and a short position in the portfolio of currencies with lower carry (P_1). Conversely, for the momentum strategy, it takes a long position in the portfolio with higher lag returns (P_3) and a short position in the portfolio of currencies with lower lag returns (P_1). Each strategy consists of a long-short portfolio, that takes a long position in P3 and short in P1.

To combine both strategies, several approaches were explored, including Mean-Variance optimization (MV), Equal-Weighted average, and Minimum Variance allocation. The analysis omitted bid-ask spreads, which represents a limitation of this strategy. Moreover, strategies overlooking bid-ask spreads, particularly in emerging markets, can result in negative Sharpe ratios, as demonstrated by Burnside et al. (2007).

2.3.3 Performance Analysis

In the analysis of the strategies, the performance for three portfolios were studied: emerging market currencies (EM), developed market currencies (DM), and then compare it to a portfolio that includes the currencies available in the two markets (Global). The strategies evaluated include the carry trade, momentum (MOM), and the combination of carry and MOM (combined strategy). Table 5 presents the Sharpe ratios for the different combined portfolio construction methods.

Table 5: *Combination of Carry and Momentum*

Sharpe Ratio			
	Minimum Variance	**MV**	**Equal-Weight**
Global	0.634	0.927	0.693
EM	0.709	0.901	0.674
DM	0.536	0.621	0.344

As expected, the mean variance optimization resulted in the highest Sharpe ratio for all portfolios, as depicted in Table 5, being the method selected for the combination of carry and MOM. Fixed weights were considered for the entire sample period, which may present limitations due to the potential for fluctuating individual asset performance and market conditions over time. The MV metric allocates a higher percentage in the momentum strategy for all portfolios. While for DM this percentage is only slightly higher, for EM and Global portfolio it is substantially greater.

Table 6 presents the performance analysis for each portfolio.

Table 6: *Descriptive Statistics*

		Excess Returns	**Volatility**	**Skewness**	**SR**	**Max Drawdown**
Carry	**Global**	-0.28%	4.73%	-0.21	-0.06	-32.73%
	EM	-0.11%	6.88%	0.38	-0.02	-45.77%
	DM	0.96%	3.38%	-0.05	0.28	-12.14%
MOM	**Global**	4.78%	5.17%	0.35	0.93	-7.60%
	EM	5.68%	6.44%	0.51	0.88	-10.15%
	DM	2.95%	5.49%	0.83	0.54	-10.11%
Combined	**Global**	4.27%	4.60%	0.29	0.93	-7.06%
	EM	4.75%	5.27%	0.49	0.90	-7.88%
	DM	2.03%	3.27%	0.40	0.62	-8.82%
Mkt-Rf		6.99%	15.94%	-0.49	0.44	-50.39%

Moreover, to have a better perception of the behavior of each strategy throughout the period, a graphic representation of the cumulative returns was elaborated (see Figure 2).

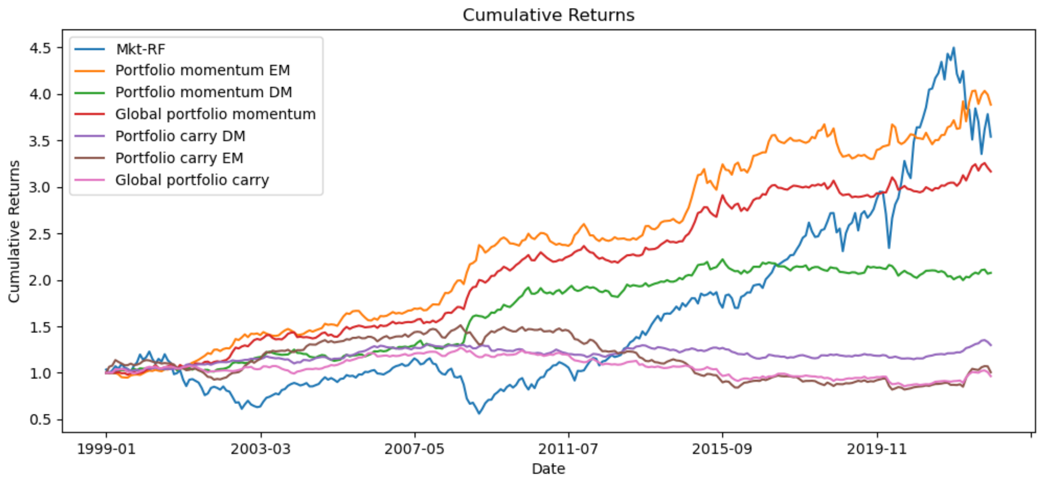

Figure 2: *Cumulative returns for Carry trade and MOM*

As illustrated in Figure 2, the carry trade resulted in the worst cumulative returns compared to other strategies. Surprisingly, all carry portfolios exhibit lower returns and consequently lower risk-adjusted returns when compared to the market factor. Only DM resulted in a positive Sharpe ratio (0.28), which was nearly half of the benchmark (Mkt-Rf). Combining both markets leads to a worse performance (Sharpe ratio of -0.06), however with lower volatility than in EM. Since the carry in EM is usually higher than for DM, the long-short strategy that involves taking long positions in EM currencies lowers the returns on the entire portfolio. In fact, Burnside et al. (2007) obtained the same result when not considering bid-ask spreads.

The MOM strategy yields good results, outperforming Carry and Mkt-Rf. The Global portfolio leads to better performance in terms of risk-adjusted returns (0.93) resulting from lower volatility (5.17%). EM has annual excess returns of 5.68%, significantly higher than for DM (2.95%). This aligns with the findings of Menkhoff et al. (2012), who observed that in high-risk countries, MOM excess returns are consistently positive and greater. Currency movements are known for being extremely skewed. In fact, the carry trade shows negative skewness values for DM and Global portfolio, however, they show less significant values than the market excess return. The MOM strategy is associated with significant positive skewness values.Therefore, investors may count on favorable results for the MOM strategy and large losses for the carry trade.

The combination of carry and MOM lead to an overall improvement in all portfolios with higher risk-adjusted returns and lower volatility in comparison to individual strategies. The Global portfolio yields higher risk-adjusted returns (0.93), outperforming all portfolios. This provides investors with significant long-term value by improving total risk-adjusted performance and more symmetric return distribution, implying that MOM could control the carry trade's exposure to external events. The combined strategy is primarily dependent on the MOM strategy, which is expected to have a major effect on its performance. The smaller allocation to carry strategies suggests a conscious effort to diversify return sources and manage risk.

The combination of both markets and techniques significantly lowers volatility and the performance is even better. Since EM are usually more volatile, a portfolio containing all currencies may help to balance the risk, as was seen in the strategy. Both conclusions are consistent with the diversification effects that may help in reduce the negative effects of fluctuations in a specific currency or strategy on the portfolio.

Furthermore, the performance of the strategies was evaluated considering the periods of the global financial crises of 2008 and the COVID-19 crises. In line with several studies, the carry trade exhibits losses when the market is highly volatile. While during the 2008 crisis, most strategies performed better than the benchmark, for the COVID crisis all strategies underperformed. This is illustrated in figure 2 with all portfolios being above the market factor. Notably, the combined strategy outperformed carry in both crises, with particularly strong performance in the 2008 crisis. This outperformance can be attributed to the adequate returns from the MOM strategy, which served to counterbalance the decline experienced by the carry strategy. Despite higher risk, investors in diverse strategies can significantly benefit from combining MOM and carry hedging techniques over the long run. Combining the two markets turned out to be a more beneficial strategy during the 2008 financial crisis, while for the COVID-19 crisis EM consistently performed better. Investing in EM offers long-term advantages with reduced risk and steady returns, in addition to help improving the portfolios during turbulent times.

2.3.4 Factor Analysis

The Fama-French (FF3) factor model is used to regress excess returns for all portfolios. Burnside et al. (2006) highlighted that conventional risk factors are insufficient to account for the carry trade results. The values obtained for the FF3 model are represented in Table 7, showing the t-statistic values in brackets.

Table 7: *FF3 Model*

		α	$\beta_{\mathbf{MKT}}$	$\beta_{\mathbf{SMB}}$	$\beta_{\mathbf{HML}}$	R^2	**IR**
Carry	**Global**	-0.187%	0.055	0.034	0.077	7.821%	-0.141
		(-2.395)	*(3.139)*	*(1.355)*	*(3.414)*		
	EM	-0.177%	0.075	0.033	0.101	6.342%	-0.091
		(-1.536)	*(2.937)*	*(0.887)*	*(3.047)*		
	DM	-0.062%	0.017	0.033	0.036	3.299%	-0.064
		(-1.073)	*(1.342)*	*(1.797)*	*(2.141)*		
MOM	**Global**	0.321%	-0.060	-0.006	-0.063	5.394%	0.217
		(3.659)	*(-3.089)*	*(-0.211)*	*(-2.497)*		
	EM	0.394%	-0.058	0.020	-0.081	4.240%	0.212
		(3.592)	*(-2.370)*	*(0.559)*	*(-2.566)*		
	DM	0.187%	-0.087	-0.010	-0.036	7.021%	0.121
		(2.029)	*(-4.256)*	*(-0.327)*	*(-1.336)*		
Combined	**Global**	0.268%	-0.048	-0.002	-0.049	4.205%	0.202
		(3.408)	*(-2.763)*	*(-0.071)*	*(-2.143)*		
	EM	0.297%	-0.035	0.022	-0.050	2.530%	0.195
		(3.279)	*(-1.750)*	*(0.752)*	*(-1.923)*		
	DM	0.066%	-0.037	0.011	-0.001	2.927%	0.071
		(1.178)	*(-2.922)*	*(0.616)*	*(-0.064)*		

In line with several studies, the FF3 model is criticized for its poor performance in explaining currency portfolio returns, with low R2 and small factor coefficients. The estimates of the market coefficient for the carry trade are small and negative, suggesting that the portfolio returns tend to follow the market's movement. However, this is only statistically significant for EM and the Global portfolio. Therefore, during periods of crises, when the market has a significant downturn, the carry strategy also leads to negative returns.

The MOM strategy exhibits a positive and statistically significant intercept across all portfolios, with EM achieving the highest abnormal returns (0.394%). The portfolios' negative and statistically significant coefficient for the market factor was observed during the 2008 crises, indicating the successful performance of the MOM strategy across all portfolios.

When combining both strategies, the negative market loading was observed for all portfolios. This observation suggests that the MOM strategy prevented negative outcomes by successfully reducing exposure to the market behavior that is inherent in the carry strategy, as demonstrated in the 2008 financial crises.

The market beta and HML factor were identified as the primary drivers of returns, with the coefficient on the HML factor positively affecting the carry trade and negatively affecting MOM and the combined strategy. In general, there was an underperformance of the carry trade relative to the benchmark due to a negative information ratio, and overperformance for the MOM and combined strategy. However, the positive values exhibit low information ratio values, indicating that despite outperforming the benchmark, it might not be by much.

2.4 Volatility Timing & Momentum in U.K. Stock Market

2.4.1 Economic Motivation

Since Jensen et al. (1972) discovered the low-volatility anomaly, the phenomenon has been deeply researched in the United States (US) and worldwide equity markets. Neo and Tee (2021) tried to improve the default low-volatility strategy by developing a timing signal based on the slope of the US volatility decile portfolio's return profile in the observed period from 1963 until 2016. Jegadeesh and Titman (1993), in their study of the momentum long/short strategy in the US from 1965 until 1989, discovered that a strategy that buys past winners and sells past losers realized a compounded excess return of 12.01%. Rabener (2020) showed that the combination of low-volatility and momentum strategies (default LOVM portfolio) has better results than the US stock market from 1989 to 2018, on an absolute return and Sharpe ratio statistics. Therefore, the adjusted LOVM portfolio, which improves the static low-volatility strategy with a volatility-based timing strategy and combines it with the momentum strategy could enhance performance.

2.4.2 Data and Methodology

The portfolio that combines volatility-based timing and momentum strategies was carried out in the United Kingdom market. The methodology involves the construction of quintile portfolios and the framework of the timing signal based on the slope of the volatility quintile return, aligning with the volatility-based timing strategy outlined by Neo and Tee (2021). Daily company data from January 1991 until December 2022 was obtained through the Compustat database. To mitigate a survivorship bias, all United Kingdom security market data has been downloaded and filtered for: United Kingdom ISINs, common shares, and pound sterling only. A subset of 4,871 companies remains for portfolio construction across the entire sample period. To account for dividends and stock returns, the daily local cumulative returns $(RI\_LOCAL)_{i,t}$ are computed as shown in Equation 4.

$$(RI\_LOCAL)_{i,t} = \frac{(PRCCD)_{i,t} \times (TRFD)_{i,t}}{(AJEXDI)_{i,t}} \tag{4}$$

Equation 4: Local cumulative return for the company i on day t, where $(PRCCD)_{i,t}$ is the local price close for company i on day t, $(TRFD)_{i,t}$ is the total return factor for company i on day t, and $(AJEXDI)_{i,t}$ is the cumulative split adjustment factor for company i on day t.

Each company's last observation of each month's variable was kept to transform the variables from daily to monthly data. For combined group strategy purposes, returns are converted into US dollars. The monthly exchange rate for GBP/USD was obtained from FRED St. Louis Fed. In each month only the top 600 based on market capitalization of securities are considered. All portfolios are rebalanced monthly, with individual portfolios weighted by market capitalization. Transaction costs are not considered. Moreover, the Fama/French European 3 Factors (FF3) dataset sourced from the Kenneth French Data Library is used to assess factor exposure and abnormal returns of the strategies. Following Bessembinder (2018), to analyze the individual volatility strategy, the sample was divided into two parts: (1) the "good" market; and (2) the "bad" market. I am using the FTSE All-Share Index (obtained through the Compustat database) as a proxy for the stock market portfolio. I assess the realized standard deviation for each security throughout the last month, employing this data to rank them into quintile portfolios based on their respective standard deviation levels. The lowest quintile is assigned to the low-volatility portfolio; the highest quintile is assigned to the high-volatility portfolio. For forming momentum portfolios, stocks are ranked by their prior 6-month cumulative return. The highest quintile is assigned to the 'winner' portfolio; the lowest quintile is assigned to the 'loser' portfolio. More specifically about the volatility-based timing strategy, the slope of the standard deviation quintile return profile as a predictor of market regimes is used (Equation 5).

$$SLOPE_m = r_{\text{high\_vol},m} - r_{\text{low\_vol},m} \tag{5}$$

Equation 5: Slope in month m, where $r_{high\_vol,m}$ is the realized return of the highest quintile portfolio in month m, and $r_{low\_vol,m}$ is the realized return of the lowest quintile portfolio in month m.

The volatility-based timing strategy holds a low-volatility portfolio by default and switches to the high-volatility portfolio when the slope parameter is statistically significantly positive for a given month, based on a t-test with a 10% significance level on rolling 12-month slope observations (Ferencz, 2022). For the combined strategy, the portfolio selected within the volatility strategy was the volatility-based timing strategy combined with the momentum portfolio. It was tested with three different approaches: (1) mean-variance optimization; (2) minimum variance; and (3) equal-weighted average. The mean-variance was selected.

2.4.3 Performance Analysis

Neo and Tee (2021) discovered that the portfolio with the highest volatility level generates greater returns during the bull market, while the low-volatility portfolio yields higher returns in "bad" market conditions. In the United Kingdom, the scenario is different. However, interesting conclusions can be drawn. Appendix A shows the naïve performance analysis for volatility quintiles in "good" and "bad" market conditions. The sample in the study includes 58% "good" and 42% "bad" months. Contrary to what is seen in the study by Neo and Tee (2021), the high-volatility quintile has better performance in terms of annual average excess returns than the low-volatility quintile in both cases. However, in terms of risk-adjusted returns, low-volatility exhibits superior performance than the high-volatility quintile in "good" market conditions, yielding a risk-adjusted return of 1.56. Significant improvements in the risk-adjusted return can be achieved by switching to a high-volatility portfolio in a given month. Table 8 represents the naïve performance analysis of strategies in the study from January 1991 until December 2022. Broadly, the risk-adjusted returns decrease from the lowest quintile to the highest quintile. The high-volatility quintile has the highest annual average excess return. However, the low-volatility quintile performs better regarding Sharpe Ratio statistics, yielding the highest value of 1.10.

Table 8: *Naïve performance analysis of strategies from January 1991 until December 2022*

Strategy	Annual Return	Volatility	Sharpe Ratio
Low Volatility	6.76%	6.16%	1.10
Q_02	7.68%	7.05%	1.09
Q_03	6.32%	8.63%	0.73
Q_04	7.48%	13.51%	0.55
High Volatility	18.88%	23.76%	0.79
Volatility Timing	9.43%	7.79%	1.21
Long Winner & Short Loser	10.48%	10.50%	1.00

As shown in Figure 3, since 1996, the volatility timing strategy has had cumulative returns superior to the low-volatility strategy, yielding an annual average excess return of 9.43% vs. 6.76% of the low-volatility quintile. Both strategies have an increasing trend in cumulative returns, with only one period in which both had a more pronounced drop (COVID-19).

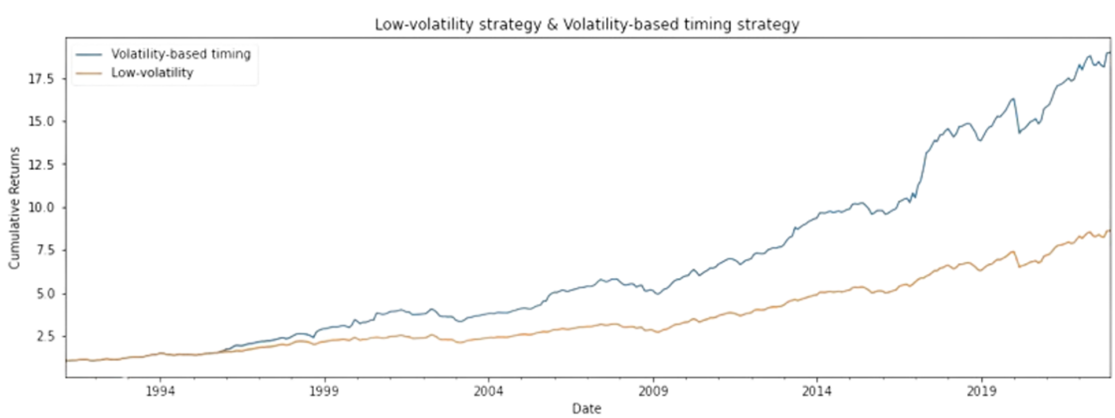

Figure 3: *Cumulative returns of the low-volatility and the volatility timing strategies*

The momentum strategy yields higher values than the low-volatility strategy, and the volatility-based timing strategy, 10.48% versus 6.76% and 9.43%, respectively. However, regarding risk-adjusted returns, the momentum strategy performs worse than the previously mentioned strategies. Table 9 shows the naïve performance analysis for a combined portfolio and Appendix B the cumulative returns of the combined portfolio, both for all sample period.

Table 9: *Naïve performance analysis of combined strategy (all sample period)*

Approach	Annual Return	Volatility	Sharpe Ratio
Mean-Variance	9.85%	7.51%	1.31
Minimum Variance	9.75%	7.48%	1.30
Equal-Weighted Average	10.07%	7.92%	1.27

Overall, the approaches had very similar performance. The equal-weighted average is the one that yields a higher annual average excess return (10.07%). As expected, the mean-variance optimization has the highest risk-adjusted return (1.31). The mean-variance approach yields better results regarding Sharpe Ratio statistics than the individual performance of each strategy, emphasizing the advantage of combining the two strategies. By comparing the default LOVM portfolio (Table 10) with the adjusted LOVM portfolio, it is clear that the second performs better in all the approaches used in this study.

Table 10: *Naïve performance analysis for Low-Volatility & Momentum (1991-2022)*

Approach	Annual Return	Volatility	Sharpe Ratio
Mean-Variance	7.94%	6.56%	1.21
Minimum Variance	6.93%	6.15%	1.13
Equal-Weighted Average	8.71%	7.38%	1.18

Excess returns were tested considering the Fama/French European 3 Factors (FF3) to consider the underlying risk factors. Table 11 shows the summarized results of the regression.

As indicated by the R^2, the model's capacity to provide an explanation for the results of the four strategies varies. The momentum strategy yields the highest R^2 (52.013%). All four portfolios provide statistically significant positive alphas at any significance level, indicating consistent excess returns compared to the expected returns based on the FF3 model. As expected, the momentum strategy has the highest alpha (0.502%), given its superior excess returns described in the naïve performance analysis. Furthermore, the strategies in the study have statistically significant positive exposure at any confidence level to the market factor (MKT). Regarding the SMB factor, Low-Volatility and Volatility-timing have positive exposure, meaning that these portfolios tend to outperform when small-capitalization stocks have worse performance than large-cap stocks. The exposure of these two portfolios for the SMB factor is not significant at any confidence level. Nevertheless, Momentum and Combined have negative exposure. The exposure of the Momentum portfolio for the SMB factor is significant at any confidence level, while the Combined is not significant at any confidence level. All except Momentum have positive sensitivity to the value factor, meaning that only Momentum's performance is negatively affected by the performance of value stocks. However, all of the portfolios are insignificant at any confidence level. All portfolios present positive information ratios, the Combined being with the highest value (0.293), meaning that this strategy consistently outperforms the other portfolios on a risk-adjusted basis, as mentioned in the naïve performance analysis.

Table 11: *FF3 regression results on each portfolio excess returns; T-stats are in parentheses*

Strategy	α	β_{MKT}	β_{SMB}	β_{HML}	R^2	IR
Low-volatility	0.275% (3.508)	0.183 (11.450)	0.062 (1.713)	0.055 (1.844)	27.964%	0.180
Volatility-timing	0.489% (4.734)	0.203 (9.609)	0.002 (0.041)	0.031 (0.776)	20.814%	0.245
Momentum	0.502% (4.617)	0.427 (19.271)	-0.220 (-4.349)	-0.063 (-1.524)	52.013%	0.233
Combined	0.493% (5.662)	0.271 (15.241)	-0.065 (-1.613)	0.002 (0.065)	39.688%	0.293

2.5 Exploiting Value Premium in U.S. Stock Market

2.5.1 Economic Motivation

Bourguignon and De Jong (2003) and Bird and Casavecchia (2007) consider value and growth investing the most popular strategies in the stock market. Value investors choose stocks with lower market value than their underlying worth, for which a price increase is predicted. On the other hand, growth investors select companies that offer strong earnings growth and have higher market price. Graham and Dodd (1934) defined value (growth) stocks as those whose price-to-book, price-to-cash flow, and price-to-earnings are low (high) compared to the market average. A (positive) value premium, or value-growth spread as defined by Capaul et al. (1993), exists when value equities beat growth companies in a given environment. Long-short strategies in these stocks allow investors to capitalize on this value premium. The systematic implementation of these strategies aims to generate alpha by strategically exploiting the perceived mispricing of value and growth stocks.

2.5.2 Data and Methodology

This research aims to analyze and improve a strategy framework intended to profit from the US stock market's value premium using three key metrics, Book-to-Market ratio (BM), EV/EBIT ratio and Revenue Growth (RevG).

The NYSE, AMEX, and NASDAQ monthly returns for common stocks with codes 10 and 11 were obtained from the CRSP database from January 1970 to December 2022. For the same period, annual company fundamentals data were obtained from Computstat.

To calculate the BM ratio, each company's book equity value (BV) was determined by subtracting the total preferred/preference stock capital (PSTK) from the sum of parent's stockholders equity (SEQ), deferred taxes and investment tax credit (TXDITC). For the EV/EBIT ratio, the EV was computed, assessing the market value of each company (MV) by multiplying the number of common shares outstanding (CSHO) with the close price (PRCC) at year-end, and then adding the net debt (ND), which was calculated by subtracting cash and short-term investments (CHE) from the sum of total long-term debt (DLTT) and total debt in current liabilities (DLC). Finally, each stock's annual earnings before interest and taxes (EBIT) was filtered to values equal to a small positive real number to avoid significant outliers. Regarding RevG metric, this was calculated as the percentage change in each company's quarterly total revenues (REVTQ). Duplicates, stocks with zero close price and outstanding common shares were eliminated to guarantee data quality and accuracy. Variables were resampled monthly using a forward-filling approach with a 12-month restriction inhibiting the look-ahead and survivorship bias.

To assess the effectiveness of both value and growth portfolios, long-only and long-short strategies using equal-weight and value-weight techniques, were created for each metric from January 1987 to December 2022. The value (growth) portfolio had lower (higher) values for RevG and EV/EBIT. The value (growth) portfolio had higher (lower) values for BM. Long-only value (growth) strategies were created by holding long the decile with the value (growth) stocks. The long-short strategies aim to assess the value premium, so the value (growth) portfolio was assigned to the long (short) leg in each parameter. The strategies were rebalanced annually based on December positions from year t-1, avoiding forward-looking bias. Moreover, transaction costs were not considered. After this, long-short strategies were created combining the three metrics, using only value-weighted long-short portfolios. Four methods were explored to perform this, Equal-Weighted Average, Minimum Variance Combination, Mean-Variance Optimization, and Aggregated Ranks Strategy.

2.5.3 Performance Analysis

Long-only and Long-short portfolios were analyzed from January 1987 until December 2022. The excess annualized returns, annualized volatilities, risk-adjusted returns, and maximum drawdowns were evaluated for each metric to identify the value premium existance. A second analysis was carried out for the four combined portfolios to analyze the various combinations of metrics. The results are presented in Table 12 and Table 13, respectively.

The strategies were split into equal-weighted and value-weighted weighting schemes. Loughran and Ritter (2000) argue that anomalous returns should vary due to different weighting techniques. Chiang (2002) stated that equal-weight portfolios consistently produce more significant estimates of portfolio returns. Regarding this sample, most strategies based on equal-weighting schemes yield better results than those with market value weights, presenting higher Sharpe Ratios. This is because value-weighted techniques invest more in stocks with higher market capitalization, which may not consider the outperformance of small-cap firms, as argued by Fama and French (1992).

Table 12: *Performance of Long-Only and Long-Short Strategies (Each Metric Individually)*

Weighting Scheme	Factor	Strategy	Returns	Volatility	SR	Max. Drawdown
Equal-Weighted	RevG	LV	2.05%	8.53%	0.24	-31.36%
		LG	4.85%	7.72%	0.63	-20.70%
		LVSG	-1.57%	1.94%	-0.81	-39.14%
	EV/EBIT	LV	14.34%	13.74%	1.04	-33.00%
		LG	4.85%	22.13%	0.22	-68.63%
		LVSG	3.17%	6.94%	0.46	-29.91%
	BM	LV	15.68%	16.29%	0.96	-38.84%
		LG	6.65%	12.66%	0.53	-30.44%
		LVSG	4.06%	5.06%	0.80	-19.90%
Value-Weighted	RevG	LV	0.70%	8.22%	0.09	-43.65%
		LG	0.90%	9.26%	0.10	-32.55%
		LVSG	-0.46%	4.10%	-0.11	-20.87%
	EV/EBIT	LV	9.79%	15.99%	0.61	-42.97%
		LG	3.53%	22.76%	0.15	-78.56%
		LVSG	1.68%	8.65%	0.19	-44.07%
	BM	LV	10.90%	18.41%	0.59	-52.01%
		LG	7.75%	16.25%	0.48	-70.74%
		LVSG	1.00%	8.81%	0.11	-43.27%

Note: *LV - Long-only value portfolio; LG - Long-only growth portfolio; LVSG - Long value portfolio and Short growth portfolio*

The portfolios based on RevG reveal the growth portfolio outperforms the value portfolio in terms of annualized excess return and Sharpe Ratio in both weighting schemes. However, looking into the other two factors, long-only value strategies outperform growth strategies in both systems of weights, indicating a value premium when sorting stocks concerning the EV/EBIT and BM. When sorting the firms for BM, the value strategies are riskier than growth strategies in both weighting schemes, as confirmed by Fama and French (1993). Nonetheless, the same is not concluded for EV/EBIT since the growth portfolio is more volatile than the value portfolio. Furthermore, in equal-weighted strategies, long-short strategy with best performance is BM, which achieves a higher Sharpe Ratio (0.80) and lower maximum drawdown of -19.90%, making it less vulnerable to losses during market downturns. In the value-weighting scheme, the long-short strategy with better performance is sorted for the EV/EBIT, with an annualized return of 1.68% and a Sharpe ratio of 0.19.

After analyzing the individual portfolios, it was also essential to construct a combination of them, described in Table 13. In the following performance analysis, only the value-weighted long-short strategies were considered.

Table 13: *Performance of Long-Short Portfolios Combined*

Strategy	Returns	Volatility	SR	Max. Drawdown
Equal-weighted Average	0.87%	5.36%	0.16	-27.50%
Minimum Variance Optimization	-0.07%	3.88%	-0.02	-14.65%
Mean Variance Optimization	1.58%	7.55%	0.21	-39.37%
Aggregated Rank	-2.41%	7.26%	-0.33	-68.65%

The Mean Variance Optimization is the strategy that yields higher annualized excess return and Sharpe ratio. However, this approach invests a 0% weight in the RevG portfolio, given its negative Sharpe Ratio, which turned out to be a pitfall, not being the one selected. Minimum Variance Optimization and Aggregated Rank Approach yield negative results, while the Equal-weighted Average method has a positive excess return (0.87%) and Sharpe Ratio (0.16). Therefore, the equal-weight approach was selected for the combination of the factors. Table 14 displays the performance statistics of the long-short strategies for different sub-periods. The aim of this analysis is to evaluate the performance of the strategies in two significant market distress conditions, the financial crisis from January 2008 to December 2009, and the COVID-19 crisis from March 2020 to December 2020.

Table 14: *Performance of Value-Weighted Long-Short Portfolios (Sub-Sample Periods)*

Sub-Sample Period	Factor	Returns	Volatility	SR	Max. Drawdown
Financial Crisis	RevG	-0.22%	4.87%	-0.046	-9.30%
	EV/EBIT	0.54%	6.29%	0.085	-1.79%
	BM	0.97%	14.21%	0.068	-8.63%
	3Factors EW	0.43%	6.34%	0.070	-2.66%
COVID-19 Crisis	RevG	0.10%	4.28%	0.023	-1.45%
	EV/EBIT	-0.66%	8.78%	-0.075	-20.05%
	BM	-0.06%	7.83%	-0.007	-4.96%
	3Factors EW	-0.20%	4.43%	-0.045	-6.59%

The COVID-19 outbreak significantly impacted the performance of portfolios, with poor performance across all strategies. However, the long-short strategy based on RevG showed a positive excess return, resulting in a value premium. The long-short strategy based on the EV/EBIT had a good behavior during the financial crisis, yielding a positive annualized excess return, the highest Sharpe Ratio (0.085), and the lower drawdown (-1.79%). Despite that, it faced difficulties in the COVID-19 crisis with the highest annualized volatility (8.78%) and maximum drawdown (-20.05%). During the financial crisis, the BM strategy delivered the greater annualized excess return (0.97%) and the highest associated risk (14.21%).

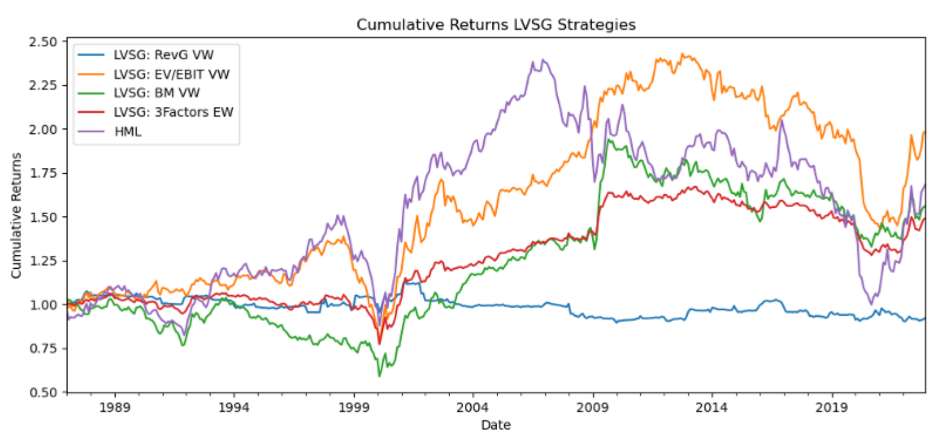

Figure 4: Long-Short Strategies Cumulative Returns

Figure 4 displays the cumulative returns of the long-short value-weighted strategies and the HML portfolio by FF3F. The long-short portfolio sorted on the EV/EBIT ratio outperforms the HML portfolio from 2009 and, compared to the other long-short strategies, is the one with the best performance in all sample period. However, the strategies experienced a significant decline due to the dot-com bubble (1999-2000), as confirmed by Asness (2020), and the COVID-19 crisis (2019-2020). Moreover, as described in Table 3, the COVID-19 outbreak reflects a vulnerability of the value premium, with a greatest impact on HML and EV/EBIT strategies. A factor analysis was developed to assess the impact of the market behavior, company size, and value characteristics on the portfolio's returns. Table 15 displays the results of the strategies' regressions against the Fama and French 3-Factor model.

Table 15: FF3F regression results on each portfolio's excess returns

Strategies	α	β_{MKT}	β_{SMB}	β_{HML}	R^2	TE	IR
LVSG: RevG	-0.247% (-4.352)	-0.017 (-1.308)	-0.032 (-1.695)	0.068 (3.745)	5.646%	0.012	-0.208
LVSG: EV/EBIT	-0.005% (-0.054)	-0.117 (-5.828)	-0.290 (-9.694)	0.320 (11.179)	46.640%	0.024	-0.002
LVSG: BM	-0.206% (-2.049)	0.026 (1.158)	0.041 (1.220)	0.495 (15.384)	35.991%	0.026	-0.080
LVSG: 3Factors	-0.152% (-2.773)	-0.036 (-2.902)	-0.094 (-5.091)	0.295 (16.709)	48.168%	0.015	-0.100

Note: *T-statistics are in parentheses. LVSG refers to long value and short growth strategies.*

All strategies are positively sensitive and statistically significant to the value factor (HML) at any conventional level, benefiting from the out-performance of value stocks compared to growth stocks. The strategy based on BM has higher exposure to the HML factor (0.495), as expected. However, the negative alphas of the four strategies suggest that they have under-performed compared to the FF3F model's predicted results. Furthermore, the BM strategy is the only one with a positive sensitivity to the MKT and SMB factors, but it is not statistically significant in both, meaning that market movements and small-cap stocks not reliable influence it, which was expected due to the use of value-weights in portfolio construction, having a higher exposure to big-cap stocks. Moreover, excluding the BM strategy, a negative exposure to the MKT factor is seen in all other strategies. However, strategies based on the EV/EBIT and EW combination have a statistically significant exposure, suggesting better performance during market downturns.

Nonetheless, this exposure is small, indicating low sensitivity to market movements. Negative IR in all strategies suggest that long-short portfolios' excess returns do not offset the additional risk implied by the positive TE's. The EW combination portfolio yields a higher R^2 (48.168%), indicating that the FF3F model explains a significant amount of the strategy's excess returns, as it combines three long-short strategies, allowing diversification and balanced exposure.

3 Combined Strategy

The aforedescribed strategies are now being considered in the creation of a combined portfolio that considers each individual strategy and respective returns are treated as an individual asset. The main goal is to evaluate the potential diversification benefits arising from integrating different asset classes (equities and currencies) and distinct geographical regions, using portfolio optimization techniques. Results are also compared to relevant benchmarks.

3.1 Individual Investment Strategies Comparison

These strategies provide insights into different aspects of the market, such as Volatility Timing & Momentum in U.K. Market (S1), Exploiting Value Premium in U.S. Stock Market (S2), Efficiency & Growth in U.S. Stock Market (S3), Investor Sentiment and Volatility Timing in European Markets (S4) and Carry & Momentum in FX Market (S5). Table 16 presents the performance statistics for the investment strategies.

Table 16: *Performance Statistics for Additional Investment Strategies*

Strategies	Ann. Return	Ann. Volatility	Skewness	Sharpe Ratio
S1	7.04%	7.68%	0.06	0.92
S2	0.32%	6.06%	-0.13	0.05
S3	7.97%	18.50%	0.18	0.43
S4	9.11%	17.64%	-0.31	0.52
S5	2.85%	4.72%	0.25	0.60

S1 stands out with a high annualized return of 7.04%, making it attractive for those seeking growth, complemented by a strong Sharpe Ratio of 0.92, indicating robust risk-adjusted performance. In contrast, S2 offers a modest annualized return of 0.32%, targeting conservative investors, yet its low Sharpe Ratio of 0.05 points to limited efficiency in balancing risk and return. Meanwhile, S3 delivers a 7.97% return, suitable for high growth seekers, and a moderate Sharpe Ratio of 0.43, offering a balance between risk and reward. S4 delivers the highest return at 9.11%, appealing to high-risk, high-reward investors, although its negative skewness suggests potential downside risks. The S5 strategy, with a steady 2.85% return and a Sharpe Ratio of 0.60, is designed for investors seeking stable, risk-adjusted returns with lower volatility. Skewness values reveal different risk profiles: S1 and S3 indicate more symmetrical returns, suggesting lower risks of extreme losses. Conversely, S4's negative skewness might pose higher risks of negative returns, requiring caution for risk-averse investors. S2's negative skewness also indicates a risk of losses, though its conservative return profile may mitigate some concerns. In summary, while S4 and S3 appeal to those seeking high returns, S1, S2 and S5 are preferable for investors prioritizing balanced risk-adjusted returns and stability.

Figure 5 provides an overview of the cumulative returns of the investment strategies.

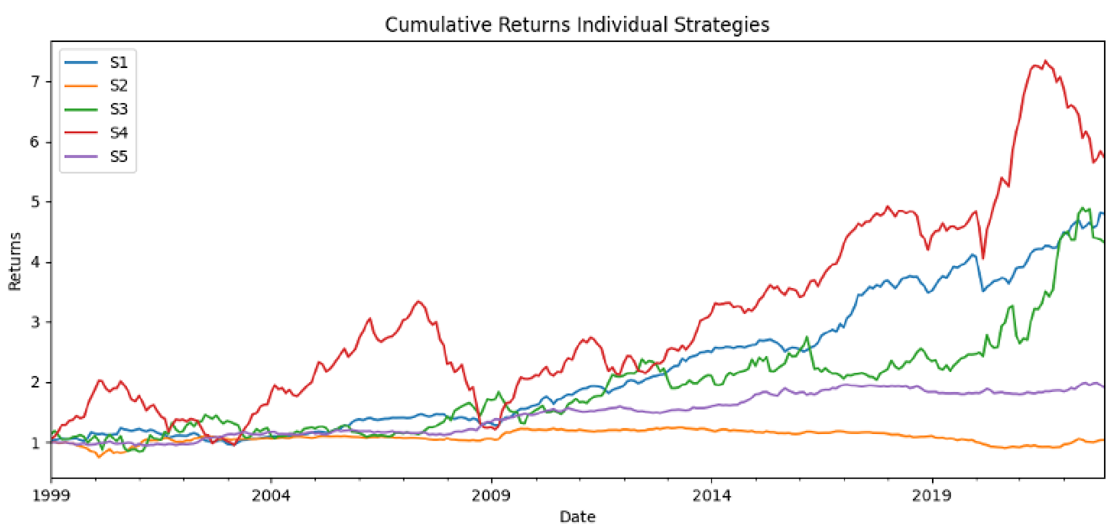

Figure 5: *Cumulative Performance Comparison*

Regarding cumulative returns, S4 outperforms the other individual strategies in most of the sample. However, as shown in Table 16, it has high volatility (17.64%) and the highest skewness (-0.31), which explains the frequent downturns of the strategy throughout the years. Moreover, despite S1 and S3 delivering similar results in terms of annualized returns and positive skewness, the higher volatility of S3 is evident in Figure 5, due to its inconsistent cumulative returns when compared to S1. Additionally, S2 and S5 are the portfolios with lower cumulative returns, as expected from the outcomes in Table 16.

Furthermore, the plot provides evidence of low correlation between the strategies, as variations in cumulative returns do not seem to closely follow each other. This provides significant diversification benefits for the combined strategy. To assess this, we build a correlation matrix in the next section.

3.2 Correlation Matrix of Portfolio Returns

The correlation matrix in Table 17 reveals important relationships between strategies, confirming the evidence provided by Figure 5.

Table 17: *Correlation Matrix of Portfolio Returns*

	S1	S2	S3	S4	S5
S1	1.00	-0.05	-0.06	0.66	-0.16
S2	-0.05	1.00	0.09	-0.16	0.05
S3	-0.06	0.09	1.00	-0.13	0.04
S4	0.66	-0.16	-0.13	1.00	-0.15
S5	-0.16	0.05	0.04	-0.15	1.00

S1 and S4 exhibit a notable positive correlation (0.66), suggesting parallel movements, but both show inverse correlations with S2, S3, and S5. S2 has a slight positive correlation with S3 (0.09), indicating some alignment in their performance. Contrastingly, S3 and S5 display almost no correlation (0.04), suggesting independent movement patterns. These insights are crucial in order to optimize portfolio diversification and risk management, as the overall low absolute value of the correlations indicates both little co-movement and significant potential diversification benefits.

3.3 Combined Portfolios Construction

After comparing the performance of the individual strategies as stand-alone portfolios and assessing how these correlate with each other, we investigate how their characteristics can be used to exploit additional value by combining them into a single portfolio. This is done exploring three different approaches: an equal-weighted (EW) Portfolio, a Tangency Portfolio (TP) and a Global Minimum Variance (GMV) Portfolio.

First, using a more naïve approach, we build an EW portfolio of the five individual strategies, by assigning a weight of one-fifth to each. The excess returns for this approach follow the equation:

$$r_t^e = \frac{1}{5} * (r_{S1,t}^e + r_{S2,t}^e + r_{S3,t}^e + r_{S4,t}^e + r_{S5,t}^e) \tag{6}$$

After implementing this simple and traditional EW approach, we turn to a more complex model that integrates the strategies into a broadly diversified portfolio using Mean-Variance (MV) analysis. This approach to portfolio optimization follows the model pioneered by Harry Markwoitz, father of modern portfolio theory, in 1952, which states that the main goal of an investment strategy is to minimize volatility (risk) for a given level of return, thus optimizing the risk-return relation and maximizing the Sharpe Ratio (SR).

The portfolio that achieves this is the Tangency Portfolio. Graphically, this portfolio is the tangency point between the Capital Market Line (CML) and the Efficient Frontier. Simulating one million different weight combinations and computing the resulting portfolio annualized return and volatility, we were able to graphically represent the Mean-Variance Frontier (see Figure 6 below). The Efficient Frontier is the subset of portfolios on the Mean-Variance Frontier that maximizes returns for each level of risk, i.e., the subset of portfolios above the GMV portfolio. The figure also represents the Tangency Portfolio, the GMV Portfolio and the CML.

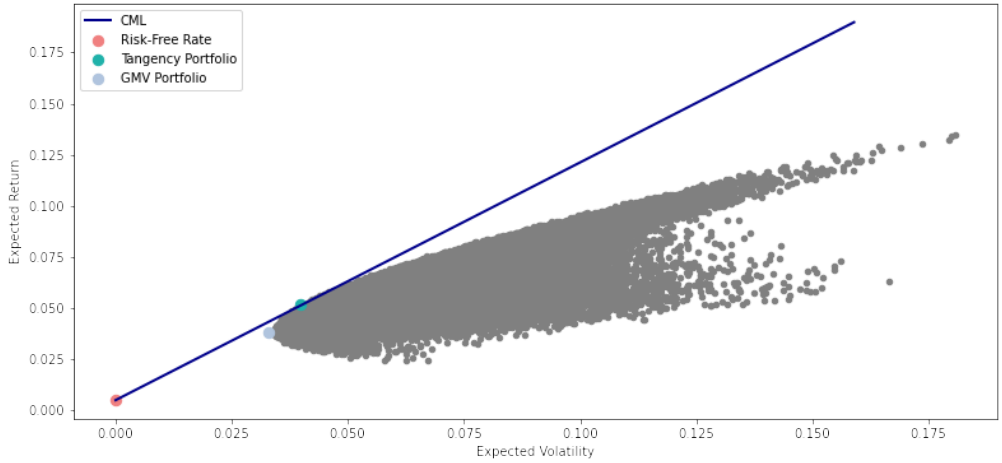

Figure 6: *Graphical representation of the CML, the Efficient frontier and the GMV and Tangency portfolios*

It is important to notice that estimating the optimal weights based on the whole sample would lead to forward-looking biased analysis. For this reason, the expected returns, variances and covariances used to estimate the weights for these portfolios refer to an in-sample period equivalent to half of the sample, from Januray 1999 to December 2010.

To find the Tangency Portfolio weights, we solve the optimization problem that maximizes the Sharpe ratio, allowing weights to vary within the interval [0;1], subject to the constraint that their sum must be equal to 1. This problem is described by:

$$\text{Maximize:} \quad \text{Sharpe Ratio} = \frac{E[R_p] - R_f}{\sigma_p}$$

Subject to:

$$\sum_{i=1}^{n} w_i = 1 \quad \text{(Sum of weights equals 1)}$$

$$0 \leq w_i \leq 1 \quad \text{(Individual weights vary between } 0 \text{ and } 1)$$

To find the GMV portfolio weights, a similar optimization problem was solved that minimizes the standard deviation of the portfolio. Despite using only positive weights (which do not allow short-selling, given the difficulties retail investors have doing it, as it requires a margin account), we also computed an unconstrained-weights version of the Tangency and GMV portfolios and used for comparison purposes only.

Furthermore, the Kenneth French Data Library was used to download Fama and French 3-Factor model (FF3F) data and Fama and French 5-Factor model (FF5F) data, encompassing the risk-free rate. These datasets were crucial for the factor analysis, which evaluates the risk exposure of the portfolios to both Fama and French models. Additionaly, the adjusted close price of iShares Core US Aggregate Bond EFT (AGG) were downloaded from Yahoo Finance website and the S&P GSCI index last prices were retrieved from Bloomberg.

In the following sections, to assess the relative performance of the strategy, we will use two benchmark portfolios. The first benchmark is the Market portfolio, pertinent because it represents the opportunity cost for the traditional long-only investor, proxied by the Fama-French $Mkt - Rf$ factor. The second benchmark portfolio is a classic 60/40 equity-bond portfolio, which is composed by 60% equities and 40% bonds. This is a broadly used type of allocation, since the returns from the two asset classes present a low and negative relationship, thus generating well diversified portfolios, which are less volatile and less exposed to big drawdowns, since income from bonds compensates equities poor performance during recessions. Despite seeming outdated for the market environment of rate cuts and low inflation during the past decade, this is a commonly used benchmark in the portfolio management industry, and with the recent rise in rates recovered potential. The equity investments are represented by the Fama-French $Mkt - Rf$ factor. Bond investments are represented by the iShares Core US Aggregate Bond ETF (AGG), that covers a comprehensive range of investment grade bonds in the US.

Finally, to enhance our analysis, we study the effect of including the returns of the S&P GSCI Index and the iShares Core US Aggregate Bond EFT (AGG) in our portfolios. In this way, a diversified Tangency Portfolio was constructed using seven portfolios: S1, S2, S3, S4, S5, GSCI, and AGG. By expanding the portfolio to include commodities and bonds alongside stocks and currencies, we seek to create a well-rounded investment strategy. This strategy recognizes that different asset classes may react differently to distinct market situations and attempts to improve risk-adjusted returns and manage portfolio risk more effectively, in order to exploit additional profitability from easily-accessible products.

3.4 Performance Analysis

3.4.1 Summary Statistics

We start by briefly analyzing the weights obtained for each combined portfolio. As mentioned before, we have constructed the portfolios allowing for negative weights and constraining them for only positive weights. The optimal weights for each of these portfolios can be found below, on Table 18.

Table 18: *Weights of Individual Strategies for the optimized portfolios*

Portfolio	S1	S2	S3	S4	S5
Tangency	27.89%	11.24%	5.90%	3.98%	50.99%
GMV	28.75%	20.88%	2.88%	0.00%	47.49%
GMV Unconstrained	29.14%	20.64%	2.81%	-0.52%	47.93%

The TP significantly weighs the S5 portfolio (50.99%). This makes sense, since it is the one that presents the lowest correlations, as it is based on a different asset class, providing more diversification benefits. The TP inherently presents only positive weights, thus suffering no changes even when unconstrained. Regarding the GMV portfolio, when considering unconstrained weights, this portfolio assigns a negative weight to S4 since it has significant volatility. In order to overcome this, a constrained GMV portfolio was constructed, allowing only positive weights. The impact on weights of the GMV portfolio was residual, with both having very similar structures. Comparing this last GMV with the TP, it assigns significantly lower weights to the S4 (0%) and S3 portfolios (2.88%), which is foreseeable since these are the most volatile portfolios. The S5 portfolio continues to be dominant (47.49%).

Now, a performance analysis is conducted on the portfolios considering excess annualized returns, annualized volatilities, risk-adjusted returns, skewness, and maximum drawdowns, as described in Table 19. We perform an In-Sample (IS), Out-of-Sample (OOS) and full sample analysis. The benchmarks are included for comparison purposes.

Table 19: *Summary Performance Statistics for Combined strategies*

	GMV			TP			EW			MKT	60/40
	IS	OOS	Full	IS	OOS	Full	IS	OOS	Full	Full	Full
ARet (%)	3.89	3.40	3.64	4.43	4.08	4.25	5.58	5.24	5.48	9.55	6.87
Vol (%)	3.46	2.95	3.21	3.71	3.22	3.47	6.28	4.87	5.61	16.04	9.91
Skew	0.05	-0.19	-0.03	0.24	-0.18	0.08	-0.10	0.11	-0.03	-0.56	-0.65
SR	1.13	1.15	1.13	1.19	1.26	1.23	0.89	1.07	0.96	0.60	0.69
MD (%)	-4.25	-6.45	-6.45	-3.02	-5.94	-5.94	-13.13	-7.64	-13.13	-51.51	-32.88

Comparing the constrained and unconstrained GMV portfolios (see Appendix C for unconstrained), both present higher Sharpe Ratios in the out-of-sample period, consistent with lower volatility (despite lower excess returns). For the in-sample analysis it resulted in lower returns and risk-adjusted returns. For both in-sample and full-sample GMV, the constrained portfolio yields higher risk-adjusted returns, which results from higher returns and similar volatility. So, since, as highlighted before, using negative weights might not always be appropriate in actual investment scenarios because short-selling can involve extra expenses and risks, we will only use the constrained GMV portfolio for further analysis.

In all sample scenarios, the GMV portfolios have generally shown lower volatility than the other portfolios, and it shows a strong risk-adjusted return. The GMV's skewness is positive in the in-sample scenario but negative in the out-of-sample and full sample scenarios which suggests that there may be a shift in the returns' distribution. Looking now into the TP, it exhibits, similarly to the GMV Portfolio, positive returns after adjusting for risk, as evidenced by its high Sharpe Ratio. The TP volatility and returns are marginally higher than those of the GMV. While all the TP scenarios have a similar performance, being higher for the out-of-sample analysis, they differ in terms of skewness. In the in-sample scenario, it delivered a positive skewness, and for the out-of-sample scenario it was negative. Although the EW Portfolio resulted in higher annualized excess returns in all sample periods, the TP is the strategy with higher risk associated, as expected. Moreover, the EW approach yields a negative skewness in-sample and positive skewness for the out-of-sample and full-sample scenarios. In this way, the Tangency Portfolio outperformed all the other strategies, with higher risk-adjusted returns for all the sample analysis.

So, according to this evaluation, the GMV has lower risk than all the other portfolios, but it also has lower returns. Investors who choose the GMV portfolio do so in order to minimize risks and maximize returns. They do this by diversifying their holdings to lower volatility and ensure that no other portfolio generates a lower risk than the one they have at this time. Nonetheless, the GMV portfolio is unable to outperform the TP. The latter is actually the best option since it has the highest Sharpe ratio, which means that we get the highest returns for each additional unit of risk. This is in accordance with our analysis, because TP achieves the best risk-adjusted performance for all sample analysis and the GMV portfolio a lower Sharpe ratio. Even though the EW portfolio achieves the highest annualized excess returns compared to the other portfolios, it also has the highest volatility, which results in lower risk-adjusted returns for all sample periods considered in the analysis.

Table 19 evidences that, when compared against the two benchmark portfolios during the full sample, all the strategies present lower returns. However, due to their lower volatility, the combined strategies beat the benchmarks in risk-adjusted performance (higher SR).

Figure 7 displays the cumulative returns of each portfolio.

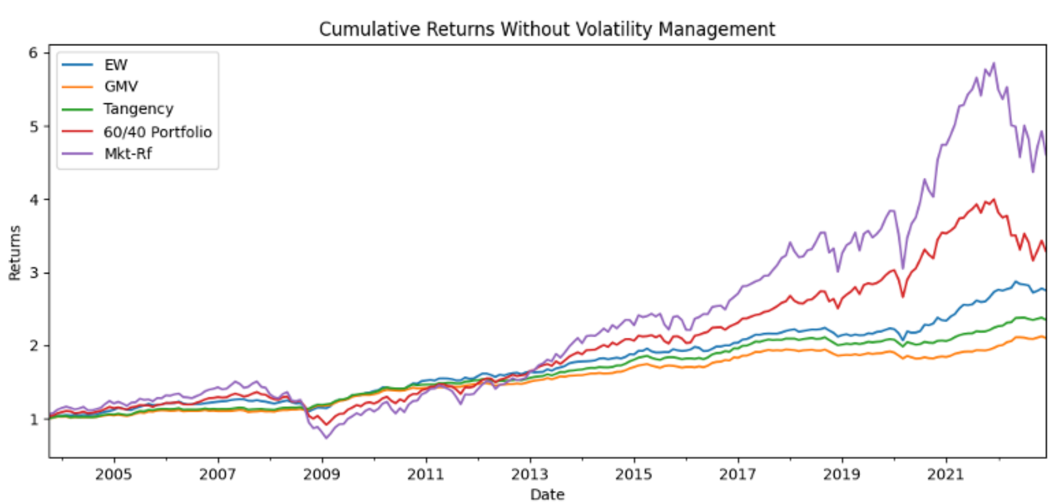

Figure 7: *Cumulative Returns without Volatility Management*

When analysing the cumulative returns, since the AGG ETF only had data available from October 2003, the cumulative analysis only starts from that date for all portfolios.

Comparing the three constructed portfolios, the EW has the highest cumulative returns, followed by Tangency Portfolio. The GMV portfolio is the one that presents the worst results in terms of cumulative returns. Until late 2008, when the global financial crisis hit the economy, the 60/40 Portfolio and the Market Portfolio exceed the other portfolios. However, after this period, the EW, Tangency Portfolio and GMV had a better performance after the crisis. A significant market recovery is evident, marked by an increase in cumulative returns since late 2009 across all portfolios. Notably, starting from late 2013, both the Market and the 60/40 Portfolios have exceeded the cumulative returns of the EW, TP and GMV Portfolios. Moreover, the COVID-19 pandemic had an impact in the cumulative returns of all portfolios, with a higher impact in the benchmarks.

To adjust cumulative returns to risk, the returns were standardized in order to achieve a volatility of 7%. Figure 8 presents the cumulative returns of the portfolios with volatility management.

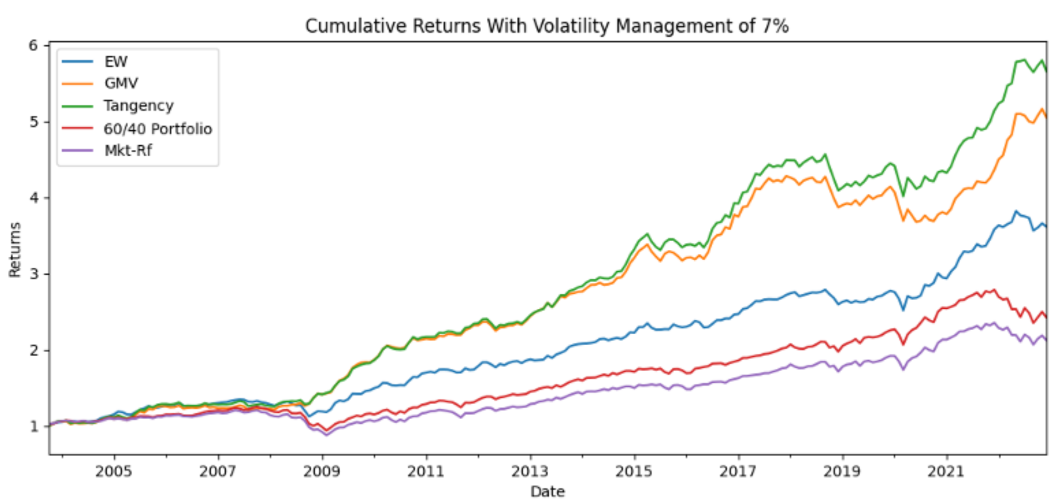

Figure 8: *Cumulative Returns with Volatility Management*

By managing the volatility to achieve a value of 7%, we can conclude that TP has the best performance in terms of risk-adjusted cumulative returns across all portfolios and benchmarks presented in the study. Contrary to what happens without volatility management, the EW portfolio performs worst among the constructed portfolios. Until the start of the global financial crisis of 2007-2008, all portfolios and benchmarks had similar performance, without any highlights, and no significant increasing trend was observed. The financial crisis had a negative impact on the two considered benchmarks and the EW portfolio. Since late 2009, an upwards trend has been observed in constructed portfolios and benchmarks. After this period, all three portfolios outperformed the two benchmarks until 2022. The Tangency and the GMV portfolios performed similarly throughout the sample. However, the start of the COVID-19 pandemic had a more significant negative impact on the GMV portfolio than on the TP. After this period, the TP recovered faster and more steeply than GMV, highlighting its best performance.

3.4.2 Drawdown Analysis

Due to the abovementioned reasons, the unconstrained GMV portfolio was not considered for the drawdown analysis. The drawdown is the peak-to-trough decline in the value of a portfolio before a new peak is achieved. Therefore, it is a measure of downside risk that informs investors about how long it takes to recover from a peak and what the maximum loss has historically been. Figure 9 shows the drawdown of the portfolios under study.

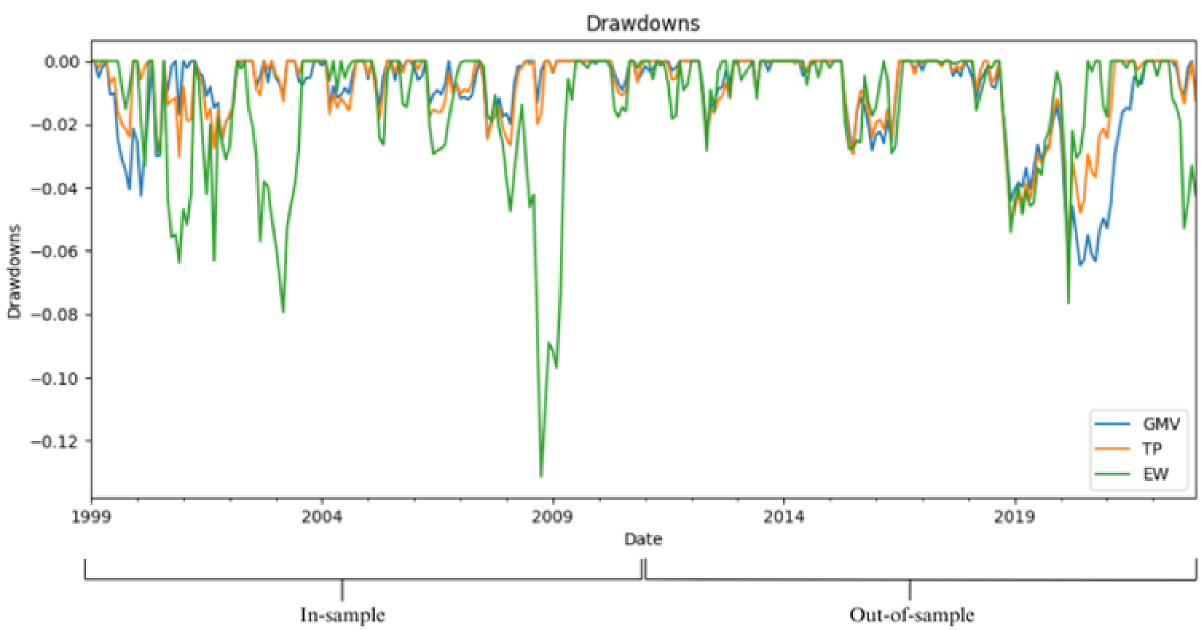

Figure 9: *Drawdowns*

The Equal-Weighted portfolio has the highest maximum drawdown (-13.13%) observed in October 2008 (in-sample), during the 2007-2008 financial crisis. On the other hand, the Tangency portfolio has the lowest maximum drawdown (-3.02%) observed in the “in-sample” period. The GMV and the Tangency portfolios in the “in-sample” period provide better security concerning downside risk than the Equal-Weighted portfolio, whose maximum drawdown is almost three times higher than the other two considered.

The Tangency portfolio had its maximum drawdown (-5.94%) in March 2020 (out-of-sample), corresponding to when the COVID-19 pandemic began to have economic consequences. Regarding the GMV portfolio, it reached its maximum drawdown (-6.45%) in June 2020 (out-of-sample) during the COVID-19 pandemic. However, it is essential to note that even in the out-of-sample, the Equal-Weighted portfolio has a higher maximum drawdown (-7.64%), reached in March 2020, than the other two portfolios considered, proving that this portfolio is the riskier as it experienced the most significant decline in value from its previous peak compared to the other two portfolios both in-sample and out-of-sample. Nonetheless, the EW portfolio needs the least time to recover from its losses, while the GMV is the portfolio that needs the most time (Table 20). It is also possible to conclude that, despite presenting the lowest volatility, the GMV has higher downside risk than the Tangency portfolio, specially during recessions.

Table 20: *Drawdown Analysis of the combined strategies*

	EW	GMV	TP
Maximum Months in Drawdown	24	47	29

3.5 Factor Analysis

A factor analysis was developed using the Fama and French 3-Factor (FF3F) and the Fama and French 5-Factor (FF5F) models, which aims to identify the underlying factors that explain the returns of the constructed portfolios.

3.5.1 Fama French 3-Factor Model

The findings of the Fama and French 3-Factor (FF3F) regression analysis on the excess returns of the portfolios for the full sample period, and for the first and second halves of the sample period are presented in Table 21. The regression coefficients (betas) for market excess risk (MKT), size premium (SMB), and value premium (HML) are reported along with the t-statistics, R^2, and Information Ratio (IR) for each portfolio.

Table 21: *Results of the FF3F model for the combined portfolios*

	Full-Sample			In-Sample			Out-of-Sample		
	EW	GMV	TP	EW	GMV	TP	EW	GMV	TP
α	0.33%	0.26%	0.30%	0.43%	0.32%	0.36%	0.23%	0.20%	0.23%
	(4.23)	*(5.24)*	*(5.59)*	*(3.35)*	*(3.96)*	*(4.33)*	*(2.63)*	*(3.27)*	*(3.48)*
β_{MKT}	0.19	0.06	0.09	0.19	0.04	0.08	0.20	0.07	0.10
	(11.25)	*(5.06)*	*(7.32*	*(7.09)*	*(2.61)*	*(4.46)*	*(10.01)*	*(5.10)*	*(6.34)*
β_{SMB}	-0.02	-0.03	-0.02	-0.01	-0.03	-0.02	-0.09	-0.06	-0.05
	(-0.61)	*(-1.97)*	*(-0.90)*	*(-0.28)*	*(-1.53)*	*(-0.71)*	*(-2.47)*	*(-2.14)*	*(-1.86)*
β_{HML}	0.05	0.06	0.02	0.00	0.03	-0.01	0.12	0.09	0.07
	(2.29)	*(3.86)*	*(1.48)*	*(-0.02)*	*(1.22)*	*(0.60)*	*(4.65)*	*(4.73)*	*(3.33)*
R^2	0.32	0.13	0.17	0.27	0.07	0.13	0.48	0.27	0.28
IR	0.25	0.30	0.33	0.29	0.33	0.37	0.21	0.26	0.29

The model varies in its capacity to explain the performance of the three portfolios, as indicated by the R^2. The EW portfolio provides the highest coefficient of determination in all periods, with the highest value in the out-of-sample period (0.48). All three portfolios provide positive statistically significant alphas at any significance level for every sample period (between 0.43% and 0.20%), indicating consistent excess returns compared to the expected returns based on the FF3F model. Unsurprisingly, the equal-weight portfolio has the highest alpha for all periods, given its superior excess returns as described in the previous performance analysis. Additionally, the three portfolios have statistically significant positive exposure to the market factor (MKT) in all sample periods. Regarding the SMB factor, a negative exposure is obtained in all periods, meaning that the portfolios tend to outperform when small-cap stocks underperform large-cap stocks. However, in the in-sample period, this exposure is not statistically significant for any of the three portfolios, being only significant in both out-of-sample and full-sample periods for the GMV and out-of-sample for the EW at a 5% confidence level. A positive sensitivity to the value factor is verified for all portfolios in all sample periods. Nonetheless, this exposure is only significant for all portfolios in the out-of-sample period and for the EW and GMV portfolios in the full-sample period. All portfolios present positive information ratios, the Tangency Portfolio being the one with highest value in all sample periods, meaning that this strategy consistently outperforms the other portfolios on a risk-adjusted basis.

3.5.2 Fama French 5-Factor Model

The Fama and French 5-Factor (FF5F) regression expands the Fama and French 3-Factor model (FF3F) to include five factors when analyzing portfolio returns. The additional factors RMW (Robust Minus Weak profitability), which implies that stocks with strong operational profitability have a better performance, and CMA (Conservative Minus Aggressive investment), indicating that stocks of firms with high total asset growth have lower returns, are included alongside the traditional market risk (MKT), size premium (SMB), and value premium (HML) factors. FF5F results are presented in Table 22

Table 22: *Results of the FF5F model for the combined portfolios*

	Full-Sample			In-Sample			Out-of-Sample		
	EW	GMV	TP	EW	GMV	TP	EW	GMV	TP
α	0.29%	0.23%	0.28%	0.36%	0.27%	0.32%	0.21%	0.20%	0.23%
	(3.54)	*(4.47)*	*(4.98)*	*(2.65)*	*(3.19)*	*(3.67)*	*(2.46)*	*(3.10)*	*(3.36)*
β_{MKT}	0.21	0.07	0.09	0.23	0.07	0.10	0.19	0.07	0.09
	(11.04)	*(5.38)*	*(7.19)*	*(6.86)*	*(3.44)*	*(4.54)*	*(9.07)*	*(4.56)*	*(5.61)*
β_{SMB}	0.01	-0.01	0.01	0.01	-0.01	0.01	-0.04	-0.03	-0.03
	(0.06)	*(-0.34)*	*(0.01)*	*(0.09)*	*(-0.06)*	*(0.07)*	*(-0.89)*	*(-1.13)*	*(-0.85)*
β_{HML}	0.02	0.04	0.01	-0.08	-0.01	-0.05	0.14	0.10	0.08
	(0.48)	*(2.08)*	*(0.47)*	*(-1.52)*	*(-0.29)*	*(-1.42)*	*(3.93)*	*(3.72)*	*(2.95)*
β_{RMW}	0.05	0.06	’0.04	0.08	0.09	0.05	0.13	0.05	0.07
	(1.52)	*(2.80)*	*(1.72)*	*(1.37)*	*(2.60)*	*(1.62)*	*(2.81)*	*(1.55)*	*(1.81)*
β_{CMA}	0.06	0.01	0.01	0.12	0.02	0.03	-0.05	-0.02	-0.04
	(1.24)	*(0.08)*	*(0.17)*	*(1.71)*	*(0.35)*	*(0.71)*	*(-0.99)*	*(-0.40)*	*(-0.88)*
R^2	0.33	0.15	0.17	0.29	0.11	0.15	0.51	0.28	0.30
IR	0.22	0.27	0.31	0.23	0.27	0.33	0.20	0.25	0.28

Similarly to the results from the previous FF3F regression, the alphas presented from the FF5F are also positive and statistically significant for all strategies in all sample periods. The FF5F has lower alphas across the portfolios and scenarios, suggesting that the additional factors account for a portion of the abnormal returns. Moreover, the R^2 shows that the model's ability to explain the performance of the three portfolios also differs along the three sample periods. However, the values are slightly higher than those obtained in the FF3F model, suggesting that the additional factors, RMW and CMA, provide a better explanation for the variability in stock excess return. As in the FF3F model, the EW combination in the out-of-sample period is the strategy with the highest coefficient of determination (0.51) in the FF5F model. Regarding the two additional factors, all strategies present positive exposure to the RMW in all sample periods. However, it is not statistically significant for the Tangency Portfolio at any period. The exposure to the CMA factor varies across portfolios and scenarios, being positive for all strategies in the full-sample and in-sample periods but negative in the out-of-sample period. Nonetheless, this exposure is not statistically significant for any strategy at any sample period. The IRs are lower in the FF5F than in FF3F, indicating that the additional factors can further explain the risk-adjusted returns of the portfolios. As in the FF3F model, the Tangency Portfolio has the highest IR in all sample periods, achieving the highest value in the in-sample period (0.33).

3.6 Diversified Portfolio

In this section, the analysis focuses on the Diversified Tangency and Global Minimum Variance Portfolios. These portfolios allow us to evaluate the influence of integrating commodities (GSCI Index) and bonds (AGG ETF) into the original TP and GMV portfolios, previously described. We seek to evaluate the impacts of these two additional asset classes on portfolio dynamics, aiming to gain insights into the enhanced risk-adjusted returns and overall performance achieved through this strategic expansion. The summary statistics of the GSCI and AGG ETF are presented below, on Table 23:

Table 23: *Performance Analysis of the GSCI and AGG indeces*

	Ann. Return	Ann. Volatility	Skewness	SR	Max. Drawdown
GSCI	8.58%	25.51%	-0.82	0.34	-71.56%
AGG	2.96%	4.19%	0.16	0.71	-17.13%

The first goal of this further investigation was to determine how the weights of the Tangency and Global Minimum Variance Portfolios change with the addition of these two asset classes. Table 24 displays the weights invested in each portfolio.

Table 24: *Weights invested in each portfolio in the Diversified Portfolios*

	S1	S2	S3	S4	S5	GSCI	AGG
TP	29.54%	0.00%	3.92%	0.00%	26.89%	3.77%	35.88%
GMV	13.69%	25.91%	2.22%	0.00%	28.88%	1.98%	27.32%

The predominant portfolios invested in TP and the GMV are the AGG (35.88% and 27.31%, respectively), S1 (29.54% and 13.69%, respectively) and S5 (26.89% and 28.88%, respectively). Looking into the Tangency Portfolio, the substantial weighting in the AGG was expected, due to the fact that bonds tend to deliver lower risk compared to the other asset classes, allowing to a more stable overall diversified portfolio and to an increased risk-adjusted return.

Analysing the GMV Portfolio, it allocates a slightly higher weight to S5 than to the AGG, which is unexpected since bonds are traditionally the lowest volatility asset class. Since the AGG and S5 have similar volatilities and risk-adjusted returns, the main reason for the slightly higher S5 weight is its greater skewness (0.25 (Table 16) vs. 0.16), which results in a distribution with a longer right tail and higher exposure to positive returns. Additionally, S5 has lower maximum drawdown (-8.16% (Table 16) vs. -17.13%) compared to AGG.

According to expectations, the incorporation of the commodities asset class (GSCI) has a small impact on the returns of both portfolios, with a weight invested of 3.77% and 1.98%, since commodities are highly volatile and often influenced by factors such as supply and demand dynamics, geopolitical events, and weather conditions. Also, commodities typically do not demonstrate a strong correlation with the other asset classes, such as stocks and bonds, which do not enhance the diversification objective.

Secondly, a performance statistics comparison between the previous Tangency Portfolio and Global Minimum Portfolio (full-samples) with the Diversified Portfolios is crucial. Table 25 summarizes the outcomes of the diversified tangency and global minimum variance portfolios.

Table 25: *Performance Analysis of the Diversified Portfolios*

	Ann. Return	Ann. Volatility	Skewness	SR	Max. Drawdown
Diversified TP	4.93%	2.95%	-0.22	1.67	-4.20%
Diversified GMV	3.11%	2.32%	0.38	1.34	-3.28%

The Diversified Tangency Portfolio delivers a noticeable higher Sharpe Ratio return when compared to the previous Tangency Portfolio, increasing from 1.26 to 1.67 (Table 19). This is the result of a slightly higher annual excess returns and lower volatility, due to the significant impact of the bond portfolio (AGG), which lowers the overall volatility of the portfolio and enhances the risk-adjusted returns. The improvement is also made clear by the lower downside risk, which decreased to -4.20%. The Diversified GMV Portfolio yields lower volatility when compared to the previous GMV (2.32% vs. 3.21% (Table 19)), corresponding to a better optimization. Additionally, the Diversified GMV Portfolio has a positive skewness (0.38 vs. -0.03 (Table 19)), meaning that this portfolio is more exposed to higher positive returns. As expected, the Diversified Tangency Portfolio provided better risk-adjusted return than the Diversified GMV Portfolio (1.67 vs. 1.34).

4 Conclusion

This study demonstrates that integrating the different individual strategies enhances performance in terms of risk-adjusted returns. This is a direct consequence of the diversification benefits that arise from the low correlation between strategies, as well as distinct return characteristics and risk exposure. The analysis reveals that during the full sample, while the equal-weighted portfolios yielded the greatest annualized excess returns (5.48%) and the GMV portfolio delivered the lowest volatility (3.21%), the Tangency portfolio outperformed them, providing the high risk-adjusted return (1.23), as expected. All portfolios performed better than the best individual strategy (S1) in terms of risk-adjusted returns (0.96, 1.13 and 1.23 *vs.* 0.96 for the EW, GMV, TP and S1, respectively).

The standout component within these portfolios is the Carry & Momentum in the FX Markets (S5) strategy, since it offers specific advantages in terms of diversification by covering a different asset class, thus having the potential to enhance the performance of the combined portfolios. The fact that the combined portfolios rely a lot on this strategy with low annualized returns (despite its good Sharpe ratio), drives the returns of the GMV and TP down as well, easily making them unattractive compared to bank deposits or fixed-income investments during periods of high interest-rates.

To further exploit diversification benefits, the construction of the diversified Tangency and Global Minimum portfolios, including the main four asset classes (equities, bonds, currencies and commodities) demonstrated markedly superior Sharpe Ratios (1.67 and 1.34 vs 1.23 and 1.13), when compared to the previous Tangency and GMV portfolios.

Summing up, the portfolios obtained are able to outperform the market in terms of risk-adjusted returns. Nevertheless, they yield lower absolute returns than the market, meaning that a leveraged position would be necessary to achieve market cumulative performance, which might not be easy for most retail investors.

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Appendix

Appendix A: Naïve performance analysis for volatility quintiles in "good" and "bad" market conditions.

Market Conditions	Quintile	Annual Return	Volatility	Sharpe Ratio
Good	Low Volatility	8.67%	5.56%	1.56
	Q_02	8.94%	7.58%	1.18
	Q_03	5.01%	11.36%	0.44
	Q_04	6.03%	17.45%	0.35
	High Volatility	14.11%	29.31%	0.48
Bad	Low Volatility	2.67%	9.77%	0.27
	Q_02	4.74%	12.62%	0.38
	Q_03	6.66%	17.49%	0.38
	Q_04	10.82%	27.39%	0.40
	High Volatility	26.47%	54.32%	0.49

Appendix B: Cumulative returns of the low-volatility and the volatility timing strategies (1991-2022)

Appendix C: Summary Performance Statistics for the Unconstrained GMV strategy

	Unconstrained GMV		
	IS	OOS	Full
ARet (%)	3.87	3.39	3.63
Vol (%)	3.46	2.95	3.21
Skew	0.04	-0.17	-0.03
SR	1.12	1.15	1.13
MD (%)	-4.46	-6.46	-6.46

1 Introduction

The VSTOXX is the Deutsche Börse implied volatility index, measuring and reflecting the market expectations of stock return volatility through the variance implied on option prices for the Euro Stoxx 50. Many academics consider the VIX, which is constructed similarly for the S&P index, the "investor fear gauge". The relation between expected volatility and market sentiment is the departure point for the analysis performed in this dissertation that explores profitability of a market-timing strategy based on expected volatility.

The initial hypothesis has two components: first, that the expected volatility (proxied by the VSTOXX) is a good indicator for European market sentiment, with high VSTOXX indicating low market sentiment and low VSTOXX indicating high market sentiment, and thus can predict performance differences between sentiment-prone and sentiment-insensitive stocks. Second, that shifts in sentiment cause short-term mispricing (over-pricing of sentiment-prone stocks when sentiment is good and under-pricing when sentiment is bad), which, due to delayed arbitrage (Abreu and Brunnermeier, 2002), persist in the short-term, leading to positive returns (in the case of over-pricing) or negative returns (in the case of under-pricing).

To test this hypothesis, portfolios of sentiment-prone stocks and portfolios of sentiment-insensitive stocks are created, and a long-only strategy that selectively goes long either the sentiment-prone portfolio (when sentiment is good) or the sentiment-insensitive portfolio (when sentiment is poor) is implemented. The choice is based on the market sentiment indicated by the VSTOXX. Results indicate that the strategy provides positive and significant returns, and can outperform the market benchmark during the sample period.

The remainder of the dissertation is organized as follows. Section 2 reviews the literature on related topics. Section 3 presents a discussion of data sources and treatment, as well as the methodology used to construct the sentiment signal and the portfolios. Section 4 presents the results and analysis of the performance. Section 5 presents the conclusions.

2 Literature Review

According to Baker and Wurgler (2007), investor sentiment can be broadly defined as “a belief about future cash flows and investment risks that is not justified by the facts at hand”. That is, irrational beliefs that deviate an asset’s value from its fundamental value.

Regarding the predictive power of investor sentiment on stock returns, Schmeling (2009) concluded that, using consumer confidence as a proxy for sentiment, for 18 industrialized countries’ sentiment is, on average and despite some variation, a significant predictor of expected returns, with a more significant power for the short and medium-term horizons. More recently, Chung et al. (2012) found further evidence that such predictive power is regime-dependent, as it is only accurate in predicting the returns of portfolios formed on firm characteristics and anomalies under economic expansion and is insignificant during recessions.

Looking into the signal of this association, diverging results are found, depending on the frequency of the sentiment indicators used. When using lower-frequency indicators, research finds that sentiment negatively forecasts future stock returns. Wang et al. (2021), use a comprehensive sample of 50 global stock markets to study this relationship, including developed and emerging economies, and conclude that sentiment has a more instant impact on the latest but a more enduring effect on developed markets. Previous research by Brown and Cliff (2005) noted that this is a normal relationship since bullish (bearish) sentiment drives stock prices above (below) their fundamental value, leading to lower (higher) future returns due to the correction of such mispricing when sentiment adjusts. Later, Baker and Wurgler (2006) supported this empirical evidence, highlighting its greater magnitude for securities whose valuations are highly subjective and difficult to arbitrage. However, when using high-frequency sentiment indicators, this relationship is positive in the short-term, pointing toward a momentary effect (Sun et al., 2016; Han and Li, 2017) that drives prices further away from the fundamental value, leading to prolonged mispricing.

One explanation for the observed short-term amplified mispricing is synchronization risks, as pointed out by Abreu and Brunnermeier (2002). According to their theory of delayed arbitrage, "rational arbitrageurs time the market, rather than correcting mispricings right away". This means that arbitrageurs ride the bubble for a while because they act without coordination and knowledge about their peers, leading to amplified mispricing and positive returns after sentiment increases. This argument is supported by evidence reported for the US market by Berger and Turtle (2015), as short-term increases in sentiment lead to positive returns, while prolonged sentiment increases lead to negative returns, demonstrating that sentiment only leads to negative returns after extended periods of overvaluation. So, one can exploit value from this short-term mispricing anomaly using good sentiment proxies.

The literature uses a myriad of measures to proxy investor sentiment, from survey data (implicit indicator) to mutual fund flows, consumer confidence indexes, and risk measures. Sentiment measures of implied volatility on stock options, like the VIX, are commonly used. In fact, Whaley (2000) classifies VIX as the "investor fear gauge", meaning that a high VIX indicates low market sentiment and vice-versa.

Looking into the European Market, the Deutsche Börse AG created, in 1999, the VSTOXX Volatility Index, computed using a methodology similar to the one used when computing the VIX, but for the EURO STOXX 50 companies. Therefore, as a comprehensive and representative measure of expected volatility in European markets, this index can be used as a sentiment proxy in Europe. In fact, Reis and Pinho (2021) show that, among others, the VSTOXX is a statistically significant proxy with a strong causality and predictability effect for stock returns in Europe. The quality of this measure is strengthened by the fact that those trading in the options market are well-informed and trained institutional investors.

Mispricing arises from limits to arbitrage, combined with investors' biased beliefs. As aforementioned, VIX and VSTOXX can represent investor sentiment and indicate limits to arbitrage. *Ceteris paribus*, in the presence of delayed arbitrage, these proxies are expected to be negatively correlated to contemporaneous mispricing and amplified returns in the medium and long-term, since high values of these indexes reflect increases in expected volatility and, consequently, greater limits to arbitrage that amplify mispricing (see Tu et al., 2016).

Looking into how stock returns vary with volatility indexes as sentiment indicators, Reis and Pinho (2021) document a significant negative effect of VSTOXX on monthly returns, meaning that higher VSTOXX leads to lower stock returns. Similarly, Guo and Qiu (2014) found strong evidence of a negative relation between VIX and future stock returns, especially for stocks with more stringent short-sale constraints.

However, Baker and Wurgler (2007) argue that some stocks (like young, small, and distressed firms) are more sentiment-prone than others, making them more attractive to speculators and challenging to arbitrage. So, sentiment is more effective at predicting differences in returns between sentiment-prone and insensitive stocks than at predicting market returns. Consistent with this view, Stambaugh et al. (2012) find that stocks more challenging to arbitrage are more sensitive to sentiment, leading to positive returns (especially following high sentiment periods) of strategies constructed based on sentiment sensitivity.

This demonstrates that there is an opportunity to explore the effect of sentiment on the cross-section mispricing effect over returns rather than on a market-wide level, since investor sentiment largely drives the cross-section of returns.

This study is also related to volatility timing. Typically, this is performed by adapting portfolio weights according to volatility predictions from GARCH models (Fleming et al., 2001). However, the presented approach is more closely linked to recent research studies on the profitability of trading strategies that time volatility by exploring the momentum caused by news-based sentiment (see Sun et al., 2016) since it uses VSTOXX as a sentiment indicator to time volatility rather than performing explicit volatility forecasts.

3 Data and Methodology

The analysis is carried out for the European stock market, proxied by 11 of its biggest economies: Germany, United Kingdom, France, Italy, Spain, Netherlands, Switzerland, Poland, Sweden, Belgium, and Russia, comprising 10761 firms. The sample period ranges from January

1999 to September 2023.

To start, I calculate the value of firm characteristics connected to the firm's exposure to arbitrage constraints and, consequently, to market sentiment. Following Ding et al. (2021), supported by Baker and Wurgler (2006) argument that sentiment-prone firms tend to be small, young, volatile, non-dividend paying, non-profitable, informationally opaque, financially distressed, and with solid growth possibilities, the computed firm-level characteristics are: firm size (ME), Age, return volatility (σ_r), earnings ratio (E/BE), dividend ratio (DIV/BE), tangible and intangible asset ratio (PP&E/A and R&D/A), book-to-market ratio (BE/ME), external finance ratio (EF/A), and Sales Growth. Computation details can be found in Appendix A. To compute these characteristics, annual firm-level accounting data was downloaded from the Compustat database from June 1997 to September 2023. Duplicates were removed to ensure the reliability of the data. The data was then resampled from annual to monthly frequency, since return data is monthly.

Monthly stock returns for the sample period are computed using daily price information extracted from Compustat. For each company, only the observations regarding their primary issue are kept. Moreover, to avoid data errors, firms with at least a price equal to zero are removed. Compustat only provides daily closing prices, so, following Jensen et al. (2023), stock split and dividend adjusted prices for firm *i* at time *t* are computed as:

$$PRCAdj_{i,t} = \frac{PRCCD_{i,t}}{AJEXDI_{i,t}} \times TRFD_{i,t} \tag{1}$$

where $PRCCD$ is the closing price for firm i at time t, $AJEXDI$ is the cumulative split adjustment factor for firm i at time t, and $TRFD$ is the daily total return factor of firm i at time t to account for cash-equivalent distributions, like dividends.

To obtain monthly returns, only month-end adjusted price observations are kept. Then, returns are computed and converted to US Dollars, for comparison purposes (Jensen et al., 2023), according to the formula:

$$Ret_{i,t} = \left(\frac{PRCAdj_{i,t}}{PRCAdj_{i,t-1}} - 1 \right) \times FX_{i,t} \tag{2}$$

where $Ret_{i,t}$ is the return for firm i at time t, and FXi, t is the exchange rate for firm i stock's quote currency at time t. Monthly exchange rate data was obtained from the FRED website. To transform these into excess returns, the risk-free rate data has been retrieved from Kenneth French Data Library. Before building the strategies, the year-end accounting data of year *t-1* is matched to monthly returns from July *t* to June *t+1*, to avoid forward-looking bias. Moreover, daily VSTOXX data for the sample period is retrieved from Qontigo's website, a Deutsche Börse company.

For each day, sentiment is defined as bad if the VSTOXX is at least 10% higher than the average of the prior 25-day historical level, and sentiment is good otherwise.

With all the data prepared, equal-weighted (EW) decile portfolios are built for each firm characteristic considered. Then, the decile portfolios are classified as prone or insensitive for each characteristic, resulting in 16 different combinations. Appendix B provides detailed information on the classification (given their multidimensional nature, as they reflect both growth and distress, BE/ME, EF/A, and Sales Growth have three different combinations of sentiment-prone and insensitive decile portfolios). Afterwards, the long-only strategy "Long VSTOXX" (LVSTOXX) is created by going long the sentiment-prone decile portfolio if sentiment is good (low VSTOXX) and going long the sentiment-insensitive decile portfolio if sentiment is bad (high VSTOXX). This strategy was then applied to each of the 16 combinations of prone and insensitive decile portfolios. To assess the relative performance of the LVSTOXX strategy, the European Market factor from the Kenneth French library is used as a benchmark, and the "Excess Long VSTOXX" (ELVSTOXX) strategy was built by subtracting the benchmark returns from the LVSTOXX strategy returns each month. Finally, an equal-weighted Aggregate portfolio of all the LVSTOXX and ELVSTOXX portfolios was computed, providing an overall idea of the behavior of the sentiment strategy.

To assess the performance of the portfolios, a naïve performance analysis using: average excess return, standard deviation, Sharpe Ratio (the three annualized) and skewness is performed. Then, to measure factor exposure and abnormal returns, I regressed the LVSTOXX returns on the Fama-French European 3 Factors and the European Momentum Factor (FF3 + Mom), a model described by:

$$r^e_{i,t} = \alpha_i + \beta_{i,M} r^e_{M,t} + \beta_{i,SMB} r^e_{SMB,t} + \beta_{i,HML} r^e_{HML,t} + \beta_{i,MOM} r^e_{MOM,t} + \epsilon_{i,t} \quad (3)$$

where $r^e_{i,t}$ is strategy i excess return in month t, $r^e_{M,t}$ is the market excess return on month t, and $r^e_{SMB,t}$, $r^e_{HML,t}$ and $r^e_{MOM,t}$ are the returns on factor zero-investment strategies mimicking size, value and momentum portfolios, respectively (see Fama and French, 1996, Carhart, 1997). The data for the factor analysis was retrieved from Kenneth French Data Library. Finally, following Chung et al. (2012) conclusion that predictive power is weak during recessions, a sub-sample performance analysis of the strategy is perfomed during the Subprime Crisis (January 2008 to March 2009) and the Covid/Ukrainian War Crisis (September 2020 to June 2023).

4 Results and Analysis

4.1 Naïve Performance Analysis

In this section, strategy results are analysed considering the average annualized excess returns (ARet), annualized volatility (Vol), the skewness (Skew), and the Sharpe Ratio (SR). ARet and Vol are presented in percentage (%). Below, Table 1 summarizes the performance of the LVSTOXX strategy (Panel A) and the excess returns of the LVSTOXX over the market benchmark (Panel B). The final column represents the success rate of the Excess LVSTOXX, computed as the fraction of days in which returns are zero or higher. The definition of the factors can be found on Appendix A.

Looking into Panel A, one can see that, overall, the LVSTOXX trading strategy is able to generate positive returns for the vast majority of portfolios, with the annualized returns ranging from 15.32% (σ_r portfolio) to -1.61% (BE/ME$_3$ portfolio). The latest is the only portfolio yielding negative returns. Regarding the risk-adjusted returns, measured by the Sharpe ratio, the values are fairly satisfactory, ranging from 0.7 (Sales Growth$_3$ portfolio) to -0.13 (BE/ME$_3$ portfolio). The profitability associated with the VSTOXX Strategy, namely for factors related to the size and value of stocks, is consistent with findings in previous literature (see Copeland and Copeland, 1999).

Most portfolios present slightly negative skews, meaning that the strategy is exposed to significant negative returns, but their distribution is close to symmetrical.

Moving to Panel B, it is clear that the LVSTOXX strategy is able to outperform the benchmark market portfolio (with four exceptions), as shown by the positive and nontrivial excess returns, which range from 9.27% (σ_r portfolio) to -6.83% (BE/ME$_3$ portfolio) and Sharpe ratios ranging from 0.62 (DIV/BE portfolio) to -0.5 (BE/ME$_3$ portfolio), yielded by the Excess LVSTOXX strategy. Moreover, the success of the Excess LVSTOXX strategy ranges from 0.41 (BE/ME$_3$ portfolio) to 0.56 (DIV/BE and ME portfolios), reflecting that the strategy generates higher returns than the benchmark, on average, in half of the months considered. Interestingly, the skewness of Excess LVSTOXX portfolios is now slightly positive, meaning that adding the short-leg on the market to the strategy increases the potential upside, reflecting that the LVSTOXX strategy has less downside risk than the market.

Table 1: *Summary Statistics for the Long-Only VSTOXX Trading Strategy*

Factor	Panel A. LVSTOXX				Panel B. Excess LVSTOXX				
	ARet	Vol	Skew	SR	ARet	Vol	Skew	SR	Success
E/BE	10.15	19.16	-0.43	0.53	4.36	11.87	0.08	0.37	*0.52*
PP&E/A	13.05	23.18	0.61	0.56	7.11	19.54	1.18	0.36	*0.53*
R&D/A	10.66	19.42	-0.70	0.55	4.84	12.79	0.17	0.38	*0.53*
EF/A$_1$	9.43	19.46	-0.68	0.48	3.67	14.11	0.15	0.26	*0.52*
EF/A$_2$	4.56	20.64	0.20	0.22	-0.96	16.07	0.71	-0.06	*0.47*
EF/A$_3$	11.28	17.93	-0.40	0.63	5.43	13.35	0.19	0.41	*0.54*
DIV/BE	13.6	20.25	-0.32	0.67	7.64	12.28	0.23	0.62	*0.56*
Age	5.38	20.66	0.23	0.26	-0.19	16.88	0.67	-0.01	*0.46*
ME	12.79	19.68	-0.22	0.65	6.86	16.94	0.56	0.40	*0.56*
BE/ME$_1$	0.26	11.10	-2.13	0.02	-5.05	13.42	0.05	-0.38	*0.44*
BE/ME$_2$	10.53	19.47	-0.85	0.54	4.71	11.55	0.09	0.41	*0.53*
BE/ME$_3$	-1.61	12.32	-2.66	-0.13	-6.83	13.54	0.11	-0.50	*0.41*
σ_r	15.32	26.82	0.65	0.57	9.27	23.55	0.84	0.39	*0.54*
Sales Growth$_1$	11.03	20.23	-0.38	0.55	5.19	14.88	0.08	0.35	*0.52*
Sales Growth$_2$	6.25	18.94	-0.17	0.33	0.65	14.60	0.35	0.04	*0.48*
Sales Growth$_3$	13.31	19.04	-0.18	0.70	7.36	14.52	0.11	0.51	*0.54*

This analysis has been carried out for Equal-Weighted portfolios. Nevertheless, using value-weighted portfolios still yields significant positive, but slightly worse, results in excess of the benchmark (see Appendix C), meaning that the returns of the strategy are not driven by the conventional size effect. To check the robustness of the LVSTOXX strategy, the returns resistance to transaction costs is evaluated. Transaction costs are set to 25 basis points, following Lynch and Balduzzi (2000), and the strategy subsists with positive returns in 14 out of the 16 factors (see Appendix D).

To assess the overall performance of the sentiment strategies, I create the EWA ggregate portfolio by equal-weighting all the previous sentiment portfolios. The overall result of trading based on sentiment is a profitable strategy, both as a stand-alone strategy (LVSTOXX) and in excess of the market benchmark (Excess LVSTOXX). Results are presented below, in Table 2.

Table 2: *Summary Statistics for an equal-weighted portfolio of all 16 LVSTOXX portfolios*

	Panel A. LVSTOXX				Panel B. Excess LVSTOXX				
	ARet	Vol	Skew	SR	ARet	Vol	Skew	SR	Success
EW Aggregate	9.03	17.55	-0.31	0.51	3.29	12.82	0.33	0.26	*0.49*

The EW Aggregate approach generates a portfolio that yields a 9.03% excess return and a 0.51 Sharpe ratio when evaluated as a stand-alone strategy (Panel A. LVSTOXX), and yields a 3.29% return and 0.26 Sharpe ratio when the benchmark portfolio returns are deducted (Panel B. Excess LVSTOXX). The skewness is close to zero in both the cases, meaning that the strategy presents reduced tail risk and low probability of extreme returns. Overall, this strategy is able to outperform the benchmark in 49% of the months. The fact that the LVSTOXX outperforms the market benchmark in less than half of the months, but is able to generate 3.29% returns in excess of the market reflects the strategy's ability to provide some downside protection when performance is poor, as well as its capacity to get significantly higher returns than the market when it outperforms.

4.2 Factor Analysis

The summary statistics presented on the naïve performance analysis suggests that the LVSTOXX strategy is profitable and outperforms the market benchmark. Nevertheless, they omit the underlying risk factors that ultimately drive the returns, leaving unclear whether the excess returns of the strategy represent a compensation for risk or not. Therefore, the excess returns of the LVSTOXX strategy were adjusted using the CAPM and the FF3 + Momentum models, described by Equation (3). The results for the α and Market factor are summarized on Table 3. Exposure to the HML, SMB and Momentum factors are documented on Appendix E.

Table 3: *LVSTOXX abnormal alphas for the CAPM and FF3 + Momentum Regressions*

Factor	Panel A. CAPM					Panel B. FF3 + Momentum				
	α (%)	*t-stat*	β_{Mkt}	*t-stat*	R^2	α (%)	*t-stat*	β_{Mkt}	*t-stat*	R^2
E/BE	5.36	*(2.40)*	0.80	*(2.67)*	0.64	6.55	*(3.30)*	0.72	*(21.80)*	0.74
PP&E/A	8.62	*(2.36)*	0.68	*(11.84)*	0.32	9.33	*(2.91)*	0.66	*(12.27)*	0.52
R&D/A	5.94	*(2.47)*	0.78	*(20.59)*	0.59	7.83	*(3.19)*	0.71	*(17.39)*	0.61
EF/A_1	5.07	*(1.92)*	0.73	*(17.66)*	0.51	6.60	*(2.81)*	0.68	*(17.24)*	0.65
EF/A_2	0.55	*(0.18)*	0.72	*(14.75)*	0.42	2.40	*(0.92)*	0.69	*(15.65)*	0.62
EF/A_3	7.03	*(2.98)*	0.68	*(18.31)*	0.53	7.84	*(3.83)*	0.63	*(18.37)*	0.68
DIV/BE	8.28	*(3.56)*	0.83	*(22.76)*	0.64	10.06	*(4.66)*	0.74	*(20.34)*	0.71
Age	1.54	*(0.48)*	0.68	*(13.46)*	0.38	4.27	*(1.53)*	0.64	*(13.60)*	0.57
ME	8.75	*(2.91)*	0.61	*(12.96)*	0.36	9.62	*(3.52)*	0.57	*(12.57)*	0.52
BE/ME_1	-1.92	*(-1.14)*	0.40	*(15.14)*	0.44	-0.48	*(-0.29)*	0.36	*(13.35)*	0.52
BE/ME_2	5.56	*(2.53)*	0.83	*(23.82)*	0.66	6.38	*(3.13)*	0.76	*(22.37)*	0.73
BE/ME_3	-4.00	*(-2.08)*	0.44	*(14.48)*	0.42	-2.53	*(-1.37)*	0.40	*(12.99)*	0.50
σ_r	10.65	*(2.41)*	0.68	*(9.73)*	0.24	12.04	*(2.96)*	0.63	*(9.26)*	0.41
Sales $Growth_1$	6.49	*(2.33)*	0.74	*(16.85)*	0.49	7.82	*(3.10)*	0.66	*(15.69)*	0.62
Sales $Growth_2$	2.33	*(0.86)*	0.69	*(16.12)*	0.47	4.44	*(1.92)*	0.64	*(16.46)*	0.65
Sales $Growth_3$	8.83	*(3.39)*	0.69	*(16.76)*	0.49	9.38	*(4.13)*	0.61	*(16.13)*	0.64
EW Aggregate	4.94	*(2.17)*	0.69	*(19.10)*	0.55	6.35	*(3.23)*	0.63	*(19.20)*	0.70

The results are, in general, consistent between the two models, and most portfolios present alphas that are smaller than the excess returns from the LVSTOXX strategy, suggesting that the good performance of the strategy is partly driven by additional risk. Moreover, the overall high R^2's, and statistically significant coefficients of risk factors (see Appendix E) associated with both models, indicate these have good explanatory power over the variability of portfolio's returns, meaning the strategy is closely associated with the risk factors. Given the consistency in results between the two models, the subsequent analysis will focus on the FF3 + Momentum model, since it is the most complete.

Controlling for these risk factors has different impacts on the profitability of strategy, depending on the analysed portfolio. For 5 out of the 16 portfolios, the profitability of the strategy is eliminated, since the alphas are statistically insignificant at all conventional significance levels. For the other factors, the alphas are positive and highly significant, meaning that adjusting for risk mitigates but does not eliminate the profitability of the strategy in these cases. The persistency of the abnormal returns for these 11 portfolios is reinforced by the high value of the information ratio, that represent the excess return relative to the benchmark per unit of risk, which averages 0.73.

The Aggregate EW portfolio generates high (4.94% for the CAPM and 6.35% for the FF3 + Mom) and statistically significant alphas, demonstrating that the sentiment strategy is able to deliver good overall results. A high R^2 (0.70) reinforces the credibility of the profitability, since the risk factors considered are able to explain most of the variation of returns.

Through this factor analysis it is reasonable to conclude that, overall, the Aggregate portfolio α provides evidence in favor of the profitability of the strategy. However, there is considerable variability in the significance of the alphas through the 16 portfolios, suggesting that the ability to create α relies partially on the factor chosen to construct the portfolio. This damages the robustness of the strategy, since it is unable to efficiently generate statistically significant abnormal returns across all portfolios.

Additionally, the positive and statistically significant exposure displayed by all portfolios to the market factor (documented on Table 3) provides evidence that the strategy has great exposure to market fluctuations, indicating some incapacity to provide hedge against the market. Given the long-only nature of the strategy this is not surprising, since long-only portfolios typically carry higher volatility and greater exposure to systematic risk than other types of portfolios (see Jacobs et al., 1993). Exposure to the SMB, HML and Momentum factors is consistently negative, positive and negative, respectively.

4.3 Subsample Analysis

As aforementioned, sentiment's predictive power tend to weaken during recessions. Therefore, in this section, cumulative return and subsample analysis during bear market periods (the Subprime and the Covid/Ukranian War Crisis) are performed. The analysis is performed for the LVSTOXX strategy, using the Age, Sales Growth$_3$, BE/ME$_1$ portfolios, and EW Aggregate portfolio, since these represent different characteristics and allow for a comprehensive analysis of the full range of portfolios.

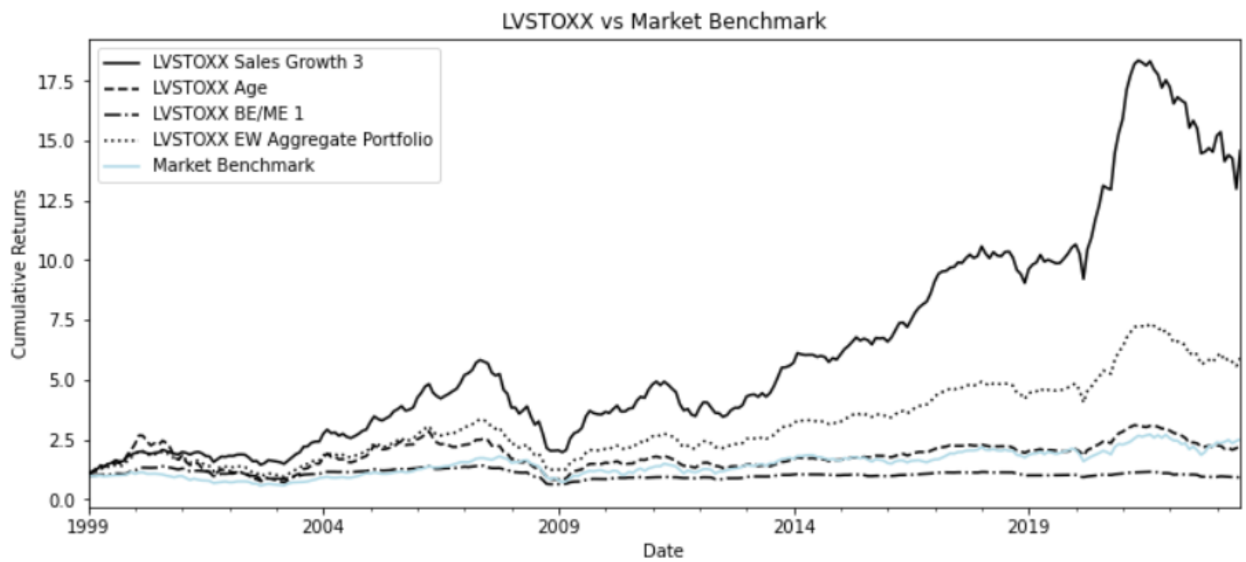

Figure 1: *Cumulative returns of LVSTOXX strategies against the market portfolio*

From Figure 1, it becomes clear that the performance of the LVSTOXX strategy is highly dependent on market conditions, partly due to the inefficiency of sentiment's predictive power (Chung et al., 2012). In fact, it is notorious how closely the strategies cumulative returns follow the market trend, evidencing high correlation, albeit with different magnitudes. Since it aggregates all 16 sentiment portfolios, the correlation of the EW Aggregate portfolio with the market is particularly relevant. As expected, the four portfolios depicted suffer major drawdowns during recessions, providing no hedge against extreme events (as hypothesized on the factor analysis), but performed notoriously well during bullish markets.

The differences in the magnitude of variation of cumulative returns are suggestive of possible capacity of the sentiment strategies to outperform the benchmark during distress periods, despite the overall poor performance. Looking into Table 4, it is noticeable how the LVSTOXX strategy outperforms the market benchmark during the Subprime crisis, with an Aggregate excess return of 3.8% and a slim Sharpe ratio of 0.20, given the high volatility. However, this is not the case for the Covid and Ukrainian War, during which the sentiment portfolios under-perform the benchmark, with an Aggregate excess return of -6.42% and a Sharpe ratio of -0.47. The fact that there was a period of bullish market during the Covid crisis, along with seemingly contradictory lower success rates and higher returns during the Subprime, suggest that the strategy is able to protect against downside risk during prolonged recessions, but has poor predictive power during regime-switching periods.

Another possible explanation for such a different behavior is the differences in liquidity. During the Covid crisis, fiscal and monetary authorities intervention provided liquidity to the market and allowed stocks to keep performing well despite the bad sentiment that existed, thus making the strategy flawed and leading to poor results. This was not the case during the Subprime crisis, as intervention was smaller and liquidity fell.

Table 4: *Summary Statistics for the Excess LVSTOXX strategy during recessions*

Factor	Panel A. Subprime				Panel B. Covid/Ukranian War			
	ARet	Volatility	SR	Success	ARet	Volatility	SR	Success
BE/ME$_1$	9.80	19.25	0.51	*0.47*	-11.25	16.79	-0.67	*0.44*
Age	3.80	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*
Sales Growth$_3$	2.10	19.09	0.11	*0.33*	-7.63	15.90	-0.48	*0.50*
EW Aggregate	3.80	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*

These conclusions can be extended to the remaining portfolios. The LVSTOXX strategy performs poorly during the Subprime and Covid/Ukrainian War crisis, with increased volatility and yielding negative returns in all portfolios on the first (see Appendix F). The Excess LVSTOXX strategy keeps the pattern described above, performing better during the Subprime crisis than in the Covid crisis for all portfolios (see Appendix G).

5 Conclusion

The literature on investor sentiment is vast. Evidence on its predictive power and association with future stock returns is not always consensual, with significant variations according to the sentiment measure and data frequency used. Nonetheless, it is possible to exploit value and generate alpha from strategies based on sentiment.

In this dissertation, the cross-sectional profitability of a long-only strategy that exploits the returns arising from amplified mispricing caused by delayed arbitrage, considering the VSTOXX as a sentiment proxy for the European stock market, is explored. The LVSTOXX strategy, applied to 16 different portfolios based on firm characteristics related to stocks' exposure to sentiment, involves holding sentiment-prone stocks when sentiment is good (low VSTOXX) and sentiment-insensitive stocks when sentiment is bad (high VSTOXX). The approach successfully generated an aggregate nontrivial excess return of 9.03% and a SR of 0.51. It generates positive and statistically significant alphas (4.94% for the CAPM and 6.35% for the FF3 + Mom model). After deducting the market benchmark, returns remain positive (3.29%) and the strategy beats the market in 49% of the months.

One characteristic in the performance of the strategy is problematic. Considering the subsample performance, it becomes clear that the strategy is highly correlated with the market, presenting very unsatisfactory performance during recessions, thus providing no hedge against extreme events. This evidence is sustained by the positive and statistically significant exposure to the market factor. Despite this great exposure, the strategy was able to outperform the market benchmark during the extended Subprime recession, providing some downside protection, but fails to do it during the Covid crisis, providing evidence of the flawed sentiments' predictive capacity during changing economical panorama.

Summing up, this dissertation contributes to the existing literature by exploring sentiment strategies on the European Market and using a different sentiment proxy. Using the VSTOXX as a sentiment indicator, the aggregate portfolio generates positive and significant alphas. There is also a positive correlation with the market, which causes poor performance during recessions, despite still being able to outperform the market during extended recession periods. Given this evidence, investors can profit from implementing the strategy in European markets, but should consider the economical context, due to its exposure to drawdowns.

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Appendix

Appendix A: *Computation details for firm characteristics*

Variable Name	Abbreviation	Computation
Earnings-to-Book-Equity Ratio	E/BE	- Earnings (E) = Income Before Extraordinary Items (CEQ) + Income Statement Deferred Taxes (TXDITC) - Preferred Dividends (DVP) - Book Equity (BE) = Shareholders' Equity (CEQ) + Balance Sheet Deferred Taxes (TXDITC)
Fixed Assets over Total Assets Ratio	PP&E/A	PP&E = Gross Property, Plant and Equipment (PPEGT) A = Total Assets (AT)
Research and Development over Total Assets ratio	R&D/A	R&D = Research and Development (XRD) A = Total Assets (AT)
External Finance over Assets	EF/A	External Finance (EF) = change in Total Assets minus change in retained earnings A = Total Assets (AT)
Dividend-to-Book-Equity Ratio	DIV/BE	Dividends (DIV) = Dividends per share at the ex date (DVPSX) * Shares outstanding (CSHO) Book Equity (BE) = Shareholders' Equity (CEQ) + Balance Sheet Deferred Taxes (TXDITC)
Firm age	Age	Number of months between the firm's first appearance on the dataset and the last available date.
Market Equity	ME	ME = Price * Shares Outstanding
Book-to-Market Ratio	BE/ME	Variables computed as mentioned above. The year-ending *t-1* ME is matched with June *t* BE
Return Volatility	σ_r	Annualized standard deviation of returns for the 12 months ending in June prior to *t*
Sales Growth	Sales Growth	$Sales\ Growth = (Sales_t - Sales_{t-1})/Sales_{t-1}$

Appendix B: *Prone and Insensitive decile considered in each portfolio*

Factor	Prone Decile	Insensitive Decile
E/BE	1	10
PP&E/A	1	10
R&D/A	10	1
EF/A$_1$	1	10
EF/A$_2$	10	5
EF/A$_3$	1	5
DIV/BE	1	10
Age	1	10
ME	1	10
BE/ME$_1$	10	1
BE/ME$_2$	1	5
BE/ME$_3$	10	5
σ_r	10	1
Sales Growth$_1$	1	10
Sales Growth$_2$	10	5
Sales Growth$_3$	1	5

Appendix C: *Summary Statistics for the Value-Weighted Excess LVSTOXX Strategy*

Factor	ARet	Vol	SR	Success
E/BE	3.74	12.98	0.29	*0.51*
PP&E/A	-7.19	26.19	-0.27	*0.46*
R&D/A	2.57	15.42	0.17	*0.52*
EF/A$_1$	1.95	13.28	0.15	*0.53*
EF/A$_2$	-6.22	14.42	-0.43	*0.46*
EF/A$_3$	2.12	12.39	0.17	*0.52*
DIV/BE	1.88	10.69	0.18	*0.55*
Age	-7.60	19.01	-0.40	*0.46*
ME	25.15	53.50	0.47	*0.50*
BE/ME$_1$	-12.37	14.38	-0.86	*0.39*
BE/ME$_2$	5.20	14.98	0.35	*0.53*
BE/ME$_3$	-11.20	14.12	-0.79	*0.39*
σ_r	7.99	22.89	0.35	*0.55*
Sales Growth$_1$	3.28	14.32	0.23	*0.52*
Sales Growth$_2$	1.38	16.01	0.09	*0.51*
Sales Growth$_3$	5.69	14.45	0.39	*0.54*

Appendix D: *Summary Statistics for the LVSTOXX Strategy with 25bp transaction costs*

Factor	ARet	Vol	SR
E/BE	6.92	18.89	0.37
PP&E/A	9.74	22.86	0.43
R&D/A	7.41	19.15	0.39
EF/A_1	6.22	19.19	0.32
EF/A_2	1.48	20.35	0.07
EF/A_3	8.02	17.69	0.45
DIV/BE	10.27	19.97	0.51
Age	2.27	20.38	0.11
ME	9.48	19.41	0.49
BE/ME_1	-2.70	10.95	-0.25
BE/ME_2	7.28	19.21	0.38
BE/ME_3	-4.52	12.15	-0.37
σ_r	11.95	26.44	0.45
Sales Growth_1	7.77	19.95	0.39
Sales Growth_2	3.12	18.69	0.17
Sales Growth_3	9.99	18.78	0.53

Appendix E: *HML, SMB and Mom Factor Loadings for the FF3 + Momentum model*

Factor	Panel A. FF3 + Momentum						
	β_{HML}	*t-stat*	β_{SMB}	*t-stat*	β_{Mom}	*t-stat*	IR
E/BE	0.02	*(0.39)*	0.76	*(9.89)*	-0.23	*(-5.38)*	0.70
PP&E/A	-0.31	*(-3.29)*	1.29	*(10.36)*	-0.19	*(-2.70)*	0.62
R&D/A	-0.01	*(-0.20)*	0.18	*(1.95)*	-0.19	*(-3.62)*	0.68
EF/A_1	-0.17	*(-2.50)*	0.89	*(9.83)*	-0.23	*(-4.58)*	0.60
EF/A_2	-0.39	*(-5.08)*	1.13	*(11.18)*	-0.24	*(-4.31)*	0.20
EF/A_3	-0.07	*(-1.10)*	0.89	*(11.22)*	-0.20	*(-4.42)*	0.81
DIV/BE	0.10	*(1.54)*	0.58	*(6.94)*	-0.27	*(-5.84)*	0.99
Age	-0.46	*(-5.66)*	1.03	*(9.53)*	-0.29	*(-4.71)*	0.32
ME	-0.16	*(-2.08)*	1.00	*(9.47)*	-0.19	*(-3.26)*	0.75
BE/ME_1	-0.12	*(-2.64)*	0.38	*(5.97)*	-0.15	*(-4.38)*	-0.06
BE/ME_2	0.05	*(0.82)*	0.66	*(8.43)*	-0.19	*(-4.30)*	0.67
BE/ME_3	-0.16	*(-2.98)*	0.44	*(6.15)*	-0.16	*(-3.94)*	-0.29
σ_r	-0.31	*(-2.60)*	1.37	*(8.74)*	-0.26	*(-2.98)*	0.63
Sales Growth_1	-0.02	*(-0.28)*	0.91	*(9.40)*	-0.26	*(-4.72)*	0.66
Sales Growth_2	-0.30	*(-4.50)*	0.97	*(10.90)*	-0.26	*(-5.24)*	0.41
Sales Growth_3	0.08	*(1.18)*	0.95	*(10.80)*	-0.22	*(-4.48)*	0.88
EW Aggregate	-0.14	*(-2.45)*	0.84	*(11.06)*	-0.22	*(-5.20)*	0.69

Appendix F: *Summary Statistics for the LVSTOXX strategy during recessions*

Factor	Panel A. Subprime			Panel B. Covid/Ukranian War		
	ARet	Volatility	SR	ARet	Volatility	SR
E/BE	-44.81	20.46	-2.19	7.40	16.44	0.45
PP&E/A	-42.75	23.49	-1.82	-3.43	14.91	-0.23
R&D/A	-34.88	22.08	-1.58	11.2	18.38	0.61
EF/A_1	-43.00	22.51	-1.91	7.50	14.15	0.53
EF/A_2	-46.80	20.99	-2.23	-5.04	12.92	-0.39
EF/A_3	-41.46	21.59	-1.92	6.83	13.94	0.49
DIV/BE	-41.75	23.19	-1.80	8.16	18.55	0.44
Age	-44.70	19.02	-2.35	-3.47	11.97	-0.29
ME	-47.76	23.88	-2.00	-3.76	11.39	-0.33
BE/ME_1	-38.44	20.45	-1.88	-3.26	7.09	-0.46
BE/ME_2	-47.94	22.72	-2.11	5.87	16.77	0.35
BE/ME_3	-43.00	22.51	-1.91	-5.93	9.12	-0.65
σ_r	-16.11	19.41	-0.83	9.74	18.73	0.52
Sales $Growth_1$	-42.44	22.34	-1.90	0.14	14.00	0.01
Sales $Growth_2$	-47.14	20.15	-2.34	1.15	14.38	0.08
Sales $Growth_3$	-42.97	22.74	-1.89	0.65	16.25	0.04
EW Aggregate	-41.98	20.38	-2.06	1.96	13.07	0.15

Appendix G: *Summary Statistics for the Excess LVSTOXX strategy during recessions*

Factor	Panel A. Subprime				Panel B. Covid/Ukranian War			
	ARet	Volatility	SR	Success	ARet	Volatility	SR	Success
E/BE	-1.03	17.17	-0.06	*0.47*	-1.39	11.58	-0.12	*0.53*
PP&E/A	2.49	27.67	0.09	*0.47*	-11.40	17.81	-0.64	*0.53*
R&D/A	15.86	13.22	1.20	*0.67*	2.14	14.27	0.15	*0.47*
EF/A_1	2.05	17.08	0.12	*0.53*	-1.30	14.44	-0.09	*0.56*
EF/A_2	-4.43	21.10	-0.21	*0.40*	-12.89	14.99	-0.86	*0.50*
EF/A_3	4.68	17.33	0.27	*0.53*	-1.92	14.77	-0.13	*0.59*
DIV/BE	4.19	16.12	0.26	*0.60*	-0.69	11.50	-0.06	*0.56*
Age	3.79	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*
ME	-6.07	26.39	-0.23	*0.33*	-11.71	15.21	-0.77	*0.50*
BE/ME_1	9.82	19.25	0.51	*0.47*	-11.25	16.79	-0.67	*0.44*
BE/ME_2	-6.39	14.52	-0.44	*0.27*	-2.81	11.71	-0.24	*0.47*
BE/ME_3	2.05	20.50	0.10	*0.40*	-13.71	16.32	-0.84	*0.41*
σ_r	47.52	42.05	1.13	*0.60*	0.77	19.25	0.04	*0.59*
Sales $Growth_1$	3.01	20.07	0.15	*0.40*	-8.10	16.20	-0.50	*0.50*
Sales $Growth_2$	-5.02	18.59	-0.27	*0.33*	-7.17	14.06	-0.51	*0.50*
Sales $Growth_3$	2.10	19.09	0.11	*0.33*	-7.63	15.90	-0.48	*0.50*
EW Aggregate	3.79	18.95	0.20	*0.40*	-6.42	13.66	-0.47	*0.50*