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Sentiment-Managed Factor Portfolios

by

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in the
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Declaration of Authorship

I, Aleksandr Mikhailov, declare that this thesis titled, 'Sentiment-Managed Parametric Portfolio Policy' and the work presented in it are my own. I confirm that:

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“Speculation becomes mortally dangerous the moment you take it seriously”

(c) Benjamin Graham, 'The intelligent Investor'

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Abstract

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This research investigates how factor timing using news sentiment can enhance the performance of investment portfolios. Specifically, it employs the Economic Policy Uncertainty (EPU) index to construct sentiment-timed versions of the five Fama-French factors: MKT, SMB, HML, RMW, and CMA over the period 1970–2020. Volatility-managed portfolios are then built for each factor and combined with the risk-free asset into a mean-variance optimal portfolio. Performance is evaluated by comparing the Sharpe Ratios of sentiment-timed portfolios against their unmanaged counterparts. Results indicate that sentiment-timed strategies generally outperform, with statistically significant improvements observed for two of the five factors at the 10% level.

Acknowledgements

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Contents

Chapter 1

Introduction

"There is a strong risk-return relationship" is the fundamental premise in finance. Moreira and Muir challenge this premise by showing that volatility-timing improves Sharpe Ratios of factor portfolios. The economic intuition of this finding lies in the ARCH effect: market volatility has high autocorrelation, while returns are not auto-correlated. Therefore, reducing portfolio exposure to risk during high market volatility improves their performance. DeMiguel, Martin-Utrera, and Raman Uppal build on this finding and show how it can be integrated into a multi-factor portfolio. The researchers show that the Sharpe Ratio of the model with volatility-timing is higher by 13% than that of the unmanaged model and that this result is statistically significant.

The unaddressed gap in the research of Moreira and Muir lies in application of other risk indicators from finance. For instance, none of the existing researches has employed the Economic Policy Uncertainty (EPU) Indicator instead of market volatility.

Current research builds on the findings of Moreira and Muir and addresses the gap by substituting market volatility with the EPU sentiment indicator. The economic intuition behind using the EPU indicator is to show that a higher volume of news about volatility and sentiment on the markets is connected to more risk. The question addressed in this research is to test whether sentiment management improves the performance of the investment portfolio as much as volatility-timing does.

Objective of this research is to find if market timing via use of news sentiment improves factor portfolio performance. To reach this objective, I formulate the following hypothesis: Sharpe Ratios of Mean-Variance combinations of Market (MKT), Small-Minus-Big (SMB), High-Minus-Low (HML), Robust-Minus-Weak (RMW), Conservative-Minus-Aggressive (CMA) factor portfolios with sentiment timing are higher than the Sharpe Ratios of factor portfolios without sentiment timing.

Motivation behind the research question is to find if market timing in form of news sentiment improves portfolio optimization. This study is significant because it expands knowledge about portfolio optimization with sentiment timing.

This master thesis is structured as follows: In Theoretical Background I discuss previous relevant researches that provide the base for this work. They cover portfolio optimization theory, volatility managed portfolios and financial sentiment indicators. The Data Description and Methodology section depicts the dataset used in the research and the model. The Empirical Findings part overviews performance of the model. Finally, the research is concluded by summarizing theoretical and practical implications, and making recommendations for future researches, as well as giving reflections on the thesis' strengths and weaknesses.

Chapter 2

Theoretical Background

This section overviews theoretical background that underpins this research. It firstly describes main findings in portfolio management theory. Then it shows how inclusion of volatility timing into portfolio optimization improves Sharpe Ratios of investment portfolios. Finally, it depicts the use of the news sentiment in financial markets.

2.1 Portfolio Management Theory

The first and simplest static asset allocation rule is Equally-Weighted portfolio. This principle is encapsulated in the ancient saying: "*One should always divide his wealth into three parts: a third in land, a third in merchandise, and a third ready to hand (cash)*" bar Aha [3]. The simplicity of this 1/N portfolio reflects its core idea of spreading risks equally across multiple assets to minimize the impact of any single asset's performance on the total wealth.

In 1950s portfolio optimization theory has shifted to Markowtiz Portfolio optimization. The researcher proved mathematically the main principle of portfolio optimization. "*diversification is a common and reasonable investment practice. Why? To reduce uncertainty! ... It seemed obvious that investors are concerned with risk and return, and that these should be measured for the portfolio as a whole,*" – claims the researcher at Nobel Prize ceremony in 1990 [25](Markowitz, H. M, 1991). Markowitz's model expands the Equally-Weighted portfolio by showing that 1/N weights equalize variance of portfolio to average covariance of included assets when their number strives to infinity. The central idea of Markowitz's model though was beyond 1/N. Hence, the model supports the ancient saying mentioned above by showing how holding uncorrelated assets improves investment portfolio. The researcher proposed to construct portfolios by optimizing tradeoff between their expected returns and expected variance-covariance matrix via changing weights allocated to assets: "*Since there were two criteria - expected return and risk - the natural approach for an economics student was to imagine an investor selecting a point from the set of Pareto optimal expected return, variance of return combinations, now known as the efficient frontier*" [25][24](Markowitz, H. M, 1952, 1991).

Being elegant theoretically, Markowitz model is limited practically. The most addressed issue associated with it is high estimation error of expected returns and covariance matrix. Estimates of expected returns based on the historical data are often unreliable, and the covariance matrix is frequently ill-conditioned. This leads to poor out-of-sample performance of Mean-Variance Optimization relative to Equally-Weighted benchmark portfolio [11](DeMiguel, Garlappi, & Uppal, 2009). The issue is typically addressed by shrinking estimates of portfolio expected returns and variance. For instance, Jobson, Korkie, and Ratti (1979) [17], Jobson and Korkie (1980)[18], and Jorion (1985, 1986)[19] [20] shrinked expected returns to weighted average of sample historical mean and a 'grand mean'. Jorion (1985, 1986) [19] [20] discards expected returns completely and solves only the task of Global Minimum-Variance portfolio optimization. Jagannathan and Ma (2003) [16] improve covariance matrix estimation by imposing short-selling constraints. Ledoit and Wolf (2003, 2004) [21] [22] shrink covariance matrix to weighted average of historical covariance matrix and 'target covariance matrix' where the latter is either a diagonal matrix of variances, or covariance where correlations of assets are assumed to be equal, or factor portfolio covariance matrix. The most successful solution was found by DeMiguel, Garlappi, Nogales, and Uppal (2009) [10] who solve Global Mean Variance portfolio optimization problem by adding regularization. The researchers show that Lasso or Ridge norm constraints stabilize the choice of weights. Their Global Mean Variance portfolio with 2-norm (Ridge) constraint beats 1/N portfolio out-of-sample by having a higher Sharpe Ratio.

The reason for poor performance of Markowitz Portfolio Optimization is "curse of dimensionality". Stepping back from the conducted researches that deal with estimation error and observing a broader picture one may realize that the estimation error is just a symptom of this disease that was discovered by Bellman, Richard Ernest (1957) [5]. Markowitz model requires estimation of parameters (expected returns, variances and covariances), hence, the problem complexity increases as the square of assets included into the model. The best of the previously mentioned solution that reduces estimation error proposed by DeMiguel, Garlappi, Nogales, and Uppal (2009) [11] still requires estimation of many parameters, hence, does not solve the stated problem ideally. As a result, Markowitz Model contains inner paradox: while addition of more assets reduces portfolio risk, it causes an exponential increase in problem complexity.

Factor-portfolios attempt to solve this problem. These models were developed by Ross (1976, 1977) [27] [28], with important advances by Huberman (1982) [14], Chamberlain (1983)[8], Chamberlain and Rothschild (1983)[9], and Ingersoll (1984)[15], Fama-French (1992)[13]. Assuming that returns of N assets can be explained by a factor model with K factors, the researcher needs to estimate 2N+2K+(N×K) parameters that stand for alpha and beta coefficients of regressions and its error terms, variances, and covariances. However, although this approach decreases the number of observations needed for model fitting, it is insufficient for large portfolios that contain over 50 assets because of the same 'curse of dimensionality'.

In contrast to factor portfolios and markowitz portfolio optimization, the elegance of the ancient $1/N$ portfolio lies in its simplicity: it requires estimation of zero parameters. As a result, it scales naturally and remains effective even for portfolios containing 10,000 assets, as its construction is entirely independent of N.

The solution that leverages the idea of model independency from N as well as Markowitz's intent to optimize the risk-return tradeoff and builds on the idea of factors as explanatory variables for assets is Parametric Portfolio Policy introduced by Brandt, Santa-Clara, and Valkanov (2009)[6]. This strategy mixes the benchmark portfolio (for example, value-weighted or equally-weighted) with K long-short firm-characteristic factor portfolios. Each of K factors determine weights of assets without optimization. Hence, the resulting portfolio contains N assets while optimization is done only across K factors. Therefore, utility maximization problem that was set up by Markowitz has only K parameters, where K is typically below 10. This is a solvable problem for the number of observations that are typically available in financial markets.

Parametric Portfolio Policy can also be viewed as generalization of 1/N portfolio discussed in the very beginning. For instance, the strategy with benchmark set to 1/N and K = 0 factors is pure equally-weighted portfolio. Addition of other factors can improve this allocation. This model shows how a benchmark index can be enhanced via use of several factors out-of-sample.

2.2 Volatility Management in Portfolio Theory

Volatility-timing strategies aim to exploit deviations in the risk-return tradeoff. Moreira and Muir (2017) [26] are pioneers of these approaches. They show that an investor can improve the Sharpe ratio of their portfolio by reducing exposure to factors during periods of high volatility. This effect persists because changes in volatility are not matched by proportional changes in expected asset returns (see Figure 1). While volatility is highly autocorrelated—and thus forecastable at short horizons—it has a weak relationship with future returns. As a result, scaling down portfolio weights in volatile periods lowers portfolio variance without significantly reducing expected returns, thereby enhancing the Sharpe ratio.

To exploit volatility-timing Moreira and Muir perform mean-variance optimization of a factor and its volatility-managed counterpart across several popular factors such as market, value, size, comparing the resulting portfolios' Sharpe Ratios with Sharpe ratios of initial factors, and by calculating alpha of the strategy. They find that volatility management significantly improves portfolio performance. Alpha of volatility-managed portfolio regressed on usual portfolios stays significant even after controlling for other factors. The authors do not give exact explanation for this phenomenon, but speculate that it can be linked to investors being less risk-averse in high volatility periods,or reacting on increase in volatility slowly.

These findings have been criticized across 3 dimensions. Cederburg, O'Doherty, Wang, and Yan (2020) [7] conclude that alphas were found in-sample. The out-of-sample Sharpe Ratios differences and alphas are insignificant. Therefore, the authors claim that volatility-managed factors do not systematically outperform unmanaged ones. Alphas found by Moreira and Muir are based on the in-sample analysis, and, therefore fall for look-ahead bias.

Barroso and Detzel (2021)[4] claim that Moreira and Muir did not account for transaction costs correctly. Factors other than market have high transaction costs, because hold large positions in small-cap stocks. Given that turnover of volatility-managed factors is up to 15 times higher than turnover of usual strategies, real transaction costs are higher than Moreira and Muir calculated.

Additional critisizm of Cederburg, O'Doherty, Wang, and Yan (2020) and Barroso and Detzel (2021)[4] towards Moreira and Muir (2017)[26] addresses outperformance of volatility-managed strategy only in high sentiment periods and fitting parameter in-sample.

DeMiguel, Martin-Utrera, and Uppal (2024)[12] show how to still profit from volatility timing by including the effects found by Moreira and Muir into Parametric Portfolio Policy model. This model addresses all criticism towards Moreira and Muir (2017) [26] and rectifies the problems of the initial paper. The researchers show that volatility-timing can be done out-of-sample, net of transaction costs, independent of sentiment periods and substituting parameter c with a better alternative. To achieve that the researchers optimize Parametric Portfolio Policy model of several factors at once instead of timing them individually. The researchers find that optimizing portfolio of several factors rectifies the problem of transaction costs, because changes in stock weights net out with each other. Additionally, while optimizing portfolio they follow the idea of Brandt, Santa-Clara, and Valkanov and account for transaction costs inside the optimization function. This approach also contributes to improved performance.

2.3 Sentiment Analysis in Financial Markets

Historically sentiment analysis saw its first uses in finance since early 2000s. Antweiler and Frank (2004) [1] used Support Vector Machines (SVMs) and Naive Bayes to classify texts at stock message boards and reveal that online forums could predict market volatility. Later on Tetlock (2007)[29] showed how negative stock market news put more downward pressure on stock prices. This research established a direct link between news and finance. Other attempts to improve sentiment models included creation of specified financial sentiment dictionaries such as Loughran's and McDonald's (2011)[23]. On contrary to usual sentiment dictionaries it was trained on 10-K reports and captured negative events in financial texts better than other sentiment dictionaries. Finally, Backer, Bloom and Davis (2019)[2] demonstrated how frequency of 'economy','stock market' and 'volatility'-related words in news correlated with the VIX index, thereby providing insights into market uncertainties. Their work highlighted the potential of using specific bags of words in news analysis to explain and predict market volatility.

EPU indicator is a relevant alternative for market volatility. This indicator is constructed on global market data and is a stationary process. Therefore, being highly correlated with market volatility the EPU indicator of Backer Bloom and Davis can serve as a proxy for market volatility in volatility-managed parametric portfolio policy model thereby forming sentiment-managed parametric portfolio policy.

Current research uses EPU indicator instead of volatility to time factor portfolios as in the research of Moreira and Muir. A further implication of these findings is inclusion of sentiment-managed factors in to the Parametric Portflio Policy model alike in the research of DeMiguel, Martin-Utrera, and Uppal on volatility-managed PPP.

Chapter 3

Methods

In this section I describe the data used for constructing the model and the process of data preparation. I firstly download Fama-French 5 factor daily and monthly data and describe it. Then I construct market volatility indicator from the market daily observations and download EPU sentiment indicator from the Backer Bloom and Davis website on sentiment management.

3.1 Data Description

I get the data for 5 factors of the stock market via Fama-French website: market factor (MKT), small-minus-big factor (SMB), high-minus-low factor (HML), robust-minus-weak factor (RMV), and conservative-minus-aggressive factor (CMA). I use the data on the US stocks from 1963 to 2024. The EPU indicator for the global data is taken directly from Backer, Bloom and Davis website.

Table 3.1 shows summary statistics on factors that are present in the dataset. It compares annualized mean return, volatility, maximum and minimum values of factor portfolios. The most well-performing factor among others is market factor. It wields 7% annual mean return. Small-minus-big is the worst performing factor across the data sample with annual mean return of 1.6%. All other factors are similar to each other and perform at a level of 3% per year on average. Volatilities of the factors are in general proportional to the mean return. For instance, market factor volatility is twice larger than its mean value. Similar proportions are spread across RMW, CMA, and SMB factors. Minimal returns achieved by factors on a daily level hit up to 17%. Maximum levels of returns spread from 2.5 to 11.3%.

Factor	μ (in %, annual)	σ (in %, annual)	Max (in %)	Min (in %)
MKT	7.078	16.185	11.3	-17.4
SMB	1.592	8.740	6.2	-11.2
HML	3.466	9.300	6.7	-5.0
RMW	3.482	6.376	4.5	-3.0
CMA	3.040	6.041	2.5	-5.9

TABLE 3.1: Summary statistics of factor returns. μ and σ are annualized.

Instead of market volatility as per the source research of Moreira and Muir, and Demiguel, Martin-Utrera, and Uppal, I use the Economic Policy Uncertainty Indicator (EPU). Economic Policy Uncertainty (EPU) measures the degree of uncertainty regarding economic policy based on newspaper coverage frequency. It tracks the number of mentions of 'Uncertainty', 'Volatility', and 'Economy' words that are mentioned in the news relative to total volume of the news in the USA across 11 newspapers: The FT, The Times and Sunday Times, The Telegraph, The Daily Mail, The Daily Express, The Guardian, The Mirror, The Northern Echo, The Evening Standard, and The Sun. The EPU indicator values are shown on figure 3.1. X-axis indicates the timeline in years from 1999 to 2024. The Y-axis indicates the level of the EPU sentiment. The higher the indicator is the greater is unpredictability about economic regulations, fiscal policy businesses, consumers, policymakers, governments. For instance, the most recent event - Trump tariffs - can be seen as a spike in the graph in 2025. Several other major shocks such as COVID-crisis and financial crisis of 2008 are also shown at the graph. The data on the EPU indicator used in this research is taken from PolicyUncertainty.com.

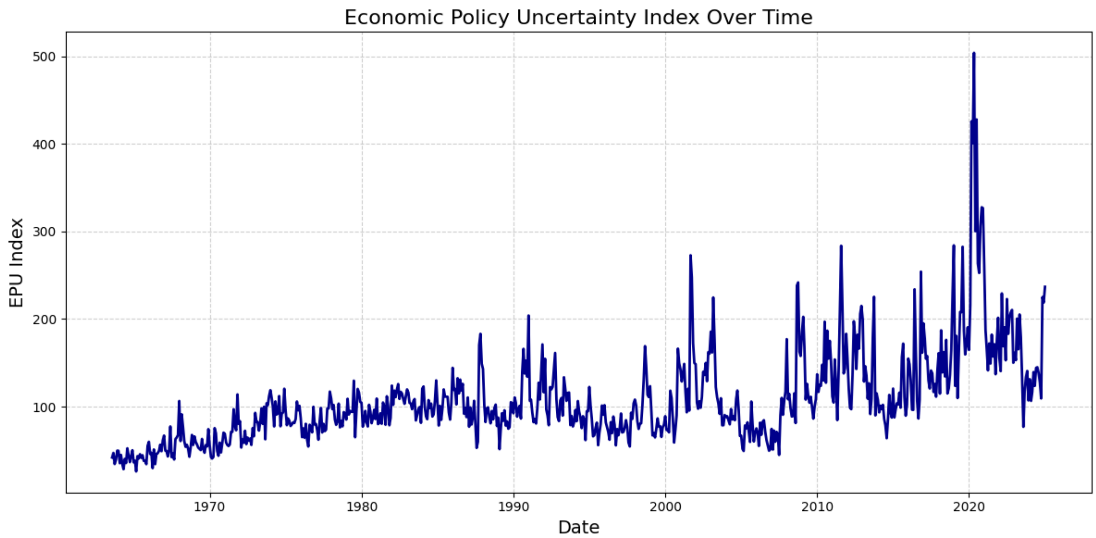

FIGURE 3.1: Economic Policy Uncertainty Index

3.2 Empirical Test

I show empirically that risk-return relationship weakens with the rise of uncertainty in news sentiment and market volatility. I use 3-bucket test to show that. For each factor I break the data down onto treciles based on the value of the EPU indicator. Then for each trecile I plot average risk-return tradeoff. Figure 3.2 shows the result. X-axis depicts various factor names and Y-axis shows average risk-return tradeoff for each factor. I observe that risk-return relationship on average weakens with rise in Economic Policy Uncertainty. This effect can be observed for every single factor in the dataset. Hence, additional risk taken in periods of high uncertainty in news is not rewarded. Therefore, there is an opportunity to exploit this caveat by timing news sentiment.

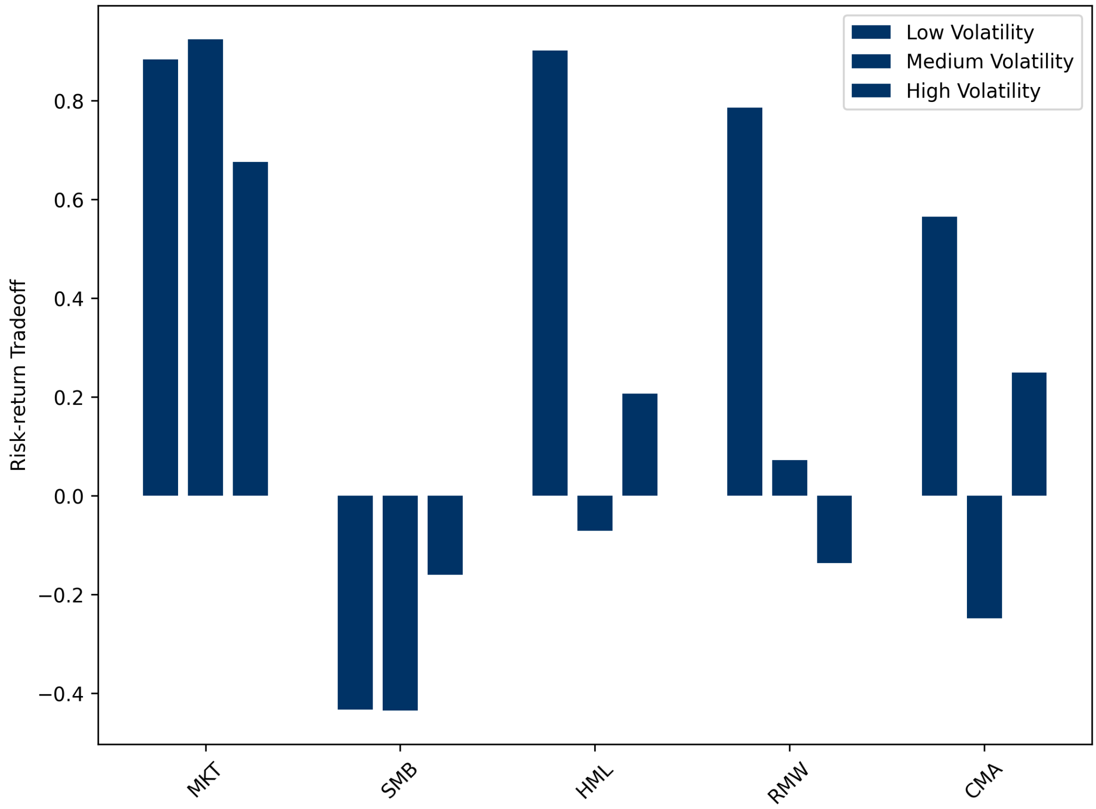

Figure 3.2: Risk-Return tradeoff for EPU buckets

Similar patterns appear at Figure 3.3, where factors are sorted by market volatility. However, unlike the clear results seen with EPU-sorted buckets, the visible effects are less pronounced. Notably, the impact is strong for the HML and CMA factors, but weaker or unclear for other factors. Therefore, the empirical test suggests that sentiment timing may be more relevant than volatility timing.

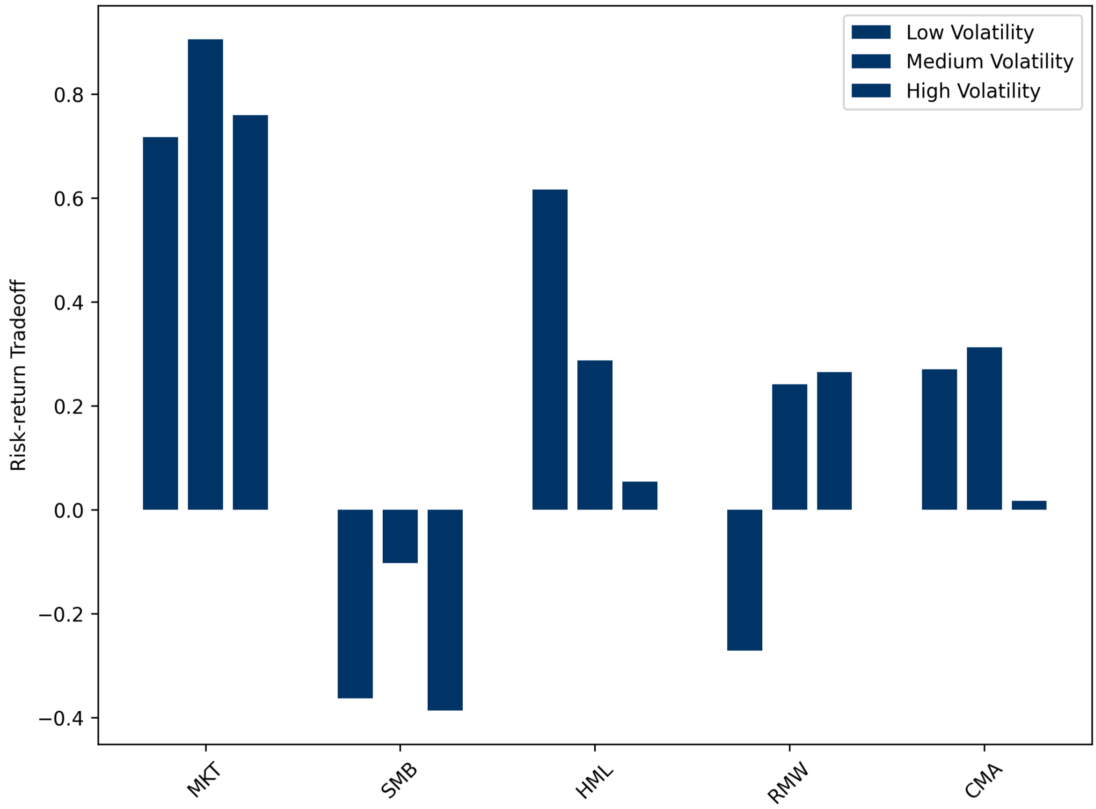

FIGURE 3.3: Risk-Return tradeoff for market volatility buckets

3.3 Methodology

This chapter depicts the model used in the research. It firstly explains volatility-managed and sentiment-managed factor construction. Then it shows how Mean-Variance portfolios of a factor, its volatility-managed (or sentiment-managed) counterpart and risk-free asset are constructed. Finally, it depicts how portfolio Sharpe Ratios are calculated and tests for differences in the Sharpe Ratios.

Moreira and Muir create volatility-managed factors by scaling a factor performance by inverse of its variance for the previous month:

$$r^{\sigma}_{t+1} = \frac{c}{\sigma^2_{m,t-1}} \cdot r_t \tag{1}$$

Where r_t is the factor return at time t (e.g., market, SMB, HML) σ^2_{t-1} is the ex-ante variance estimate based on historical returns up to $t-1$, c is a scaling factor that is used to make variances of volatility-managed and unmanaged factors equal. This research observes and compares 2 models for factor management: market-volatility-based and EPU sentiment-based. Hence, both can be written as:

$$r_{t+1}^{\sigma} = \frac{c_{EPU}}{EPU_{t-1}} \cdot r_t \tag{2}$$

$$r_{t+1}^{\sigma} = \frac{c_m}{\sigma_{mt-1}^2} \cdot r_t \tag{3}$$

Where c_{EPU} is notation for scaling of factor portfolio by EPU indicator, c_m is notation for scaling by market volatility. These parameters are found by minimizing the difference between standard deviations of factor returns. One can carry out this exercise in-sample and out-of-sample. In this research, I observe the out-of-sample calculation of the parameter c to assure a realistic approach to the problem.

Then I find performance of 2 additional investment portfolios: mean-variance portfolio of volatility-managed factor, pure factor and risk-free fund, and mean-variance portfolio of sentiment-managed factor, pure factor and risk-free fund. I assume that the weights of these 2 factors and investment in risk-free rate are equal to 1. Also, I force no short-selling constraints to the algorithm. The optimal weights are found via optimization function of scipy.optimize package for Python.

$$\begin{cases} \max\limits_{w_f, w_v, w_r} & \mu_p = w_f \mu_f + w_v \mu_v + w_r r_f \\ \text{s.t.} & \sigma_p^2 = w_f^2 \sigma_f^2 + w_v^2 \sigma_v^2 + 2 w_f w_v \rho_{fv} \sigma_f \sigma_v, \\ & w_f + w_v + w_r = 1, \\ & w_f, w_v, w_r \geq 0 \end{cases}$$

Performance of the factor portfolios is assessed via Annualized Sharpe Ratios. Sharpe Ratio shows risk-adjusted return after subtraction of the risk-free rate.

$$SR = \frac{\mu_r - R_f}{\sigma_r} \tag{4}$$

After the Sharpe Ratios are calculated I check statistical significance of the Sharpe Ratio Differences via Ledoit-Wolf Z-test.

$$Z = \frac{\widehat{SR}_n - \widehat{SR}_m}{\sqrt{\mathbb{V}\left[\widehat{SR}_n - \widehat{SR}_m\right]}} \tag{5}$$

$$\mathbb{V}\left[\widehat{SR}_n - \widehat{SR}_m\right] = \frac{1}{T}\left[2 - 2\widehat{\rho}_{nm} + \frac{1}{2}\left(\widehat{SR}_n^2 + \widehat{SR}_m^2 - 2\widehat{SR}_n\widehat{SR}_m\widehat{\rho}_{nm}^2\right)\right] \tag{3.1}$$

I test differences in Sharpe Ratios for volatility-managed and sentiment managed factor portfolio, volatility-managed and pure factor portfolio, sentiment-managed and pure factor portfolio.

Chapter 4

Empirical Findings

In this section of the research, I observe the results of the portfolio optimization process and compare Sharpe Ratios for each set of factors: pure factor portfolio, volatility-managed factor portfolio, sentiment-managed factor portfolio. The model depicted in the previous chapter uses the out-of-sample analysis capitalizing on the data from January 1963 to January 2022. The out-of-sample window is chosen to be expanding.

4.1 Volatility-Managed Factors

Figure 4.1 represents a comparison of Sharpe Ratios between the original (unmanaged) factors and their volatility-managed Mean-Vairance portfolio counterparts. The X-axis displays the five standard factors: MKT (Market), SMB (Size), HML (Value), RMW (Profitability), and CMA (Investment). The y-axis shows the Sharpe Ratio values for each factor.

For each factor, two bars are plotted: one represents the original Sharpe Ratio (blue) and the other the volatility-managed Sharpe Ratio (green). The numerical value of each Sharpe Ratio is annotated near the respective bar.

The results indicate that volatility management overall improves the risk-adjusted performance of most factors. Specifically, the Sharpe Ratio of the market factor (MKT) increases from 0.50 to 0.71. The HML and RMW factors are improved from 0.19 to 0.30 and from 0.23 to 0.31, respectively. For SMB, volatility management neutralizes a negative Sharpe Ratio of -0.59, raising it to zero. In contrast, the CMA factor experiences a decline in performance, with its Sharpe Ratio dropping from 0.19 to -0.04 after volatility adjustment. Overall, this comparison suggests that volatility management enhances the risk-return tradeoff for most of the considered equity factors.

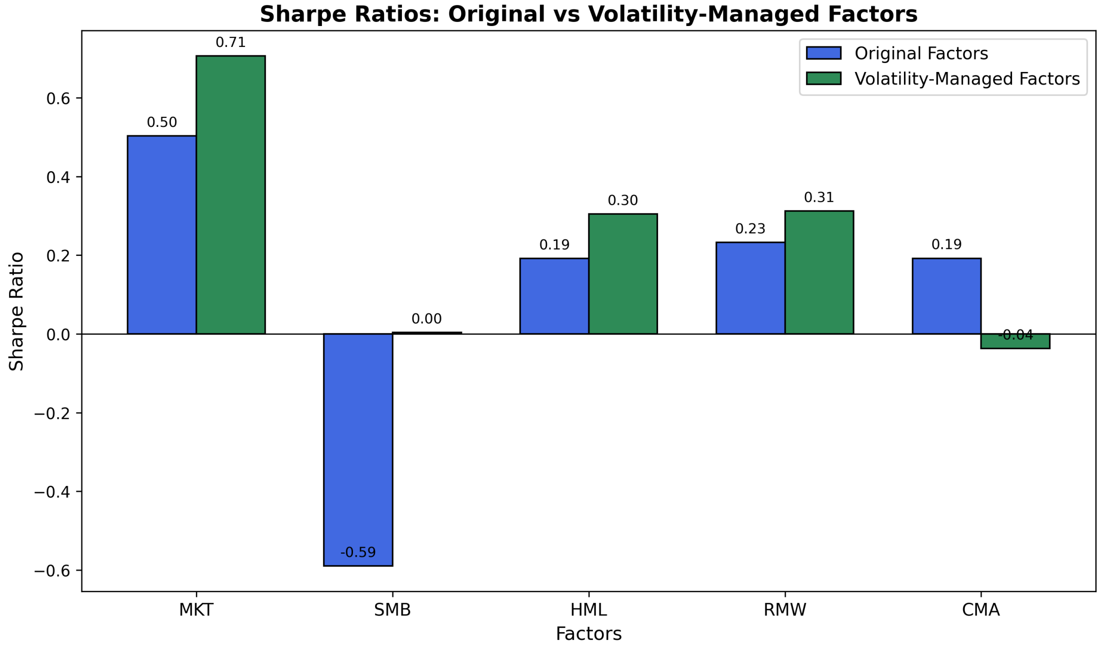

FIGURE 4.1: SR Comparison Original Factors VS Volatility-Managed factors

4.2 Sentiment-managed factors

Figure 4.2 represents a comparison of Sharpe Ratios between original (unmanaged) equity factors and portfolio of EPU-managed factor and pure factor. The x-axis displays the factor names. The y-axis reports the Sharpe Ratio for each factor. Each factor is represented by the same 2 bars as the previous graph: the blue bar shows the Sharpe Ratio of the original factor, while the green bar depicts the Sharpe Ratio of the EPU-managed version.

The results suggest that EPU-based timing on average improves risk-adjusted performance in several cases. For example, the Sharpe Ratio of the Market factor improves from 0.50 to 0.65, and the aggregated. As in the case with market volatility, the SMB factor's original Sharpe Ratio becomes positive after it has been negative in unmanaged case. HML and RMW factors also show improvements, from 0.19 to 0.30 and from 0.23 to 0.31, respectively. Overall, this figure indicates that incorporating EPU as a timing signal can enhance the performance of most factors.

4.3 Combined Comparison

Figure 4.3 shows a comparative analysis of Sharpe Ratios across all 3 versions of factor portfolios. The results demonstrate that both volatility-based and EPU-based scaling significantly enhance risk-adjusted returns across most factors. For the market factor

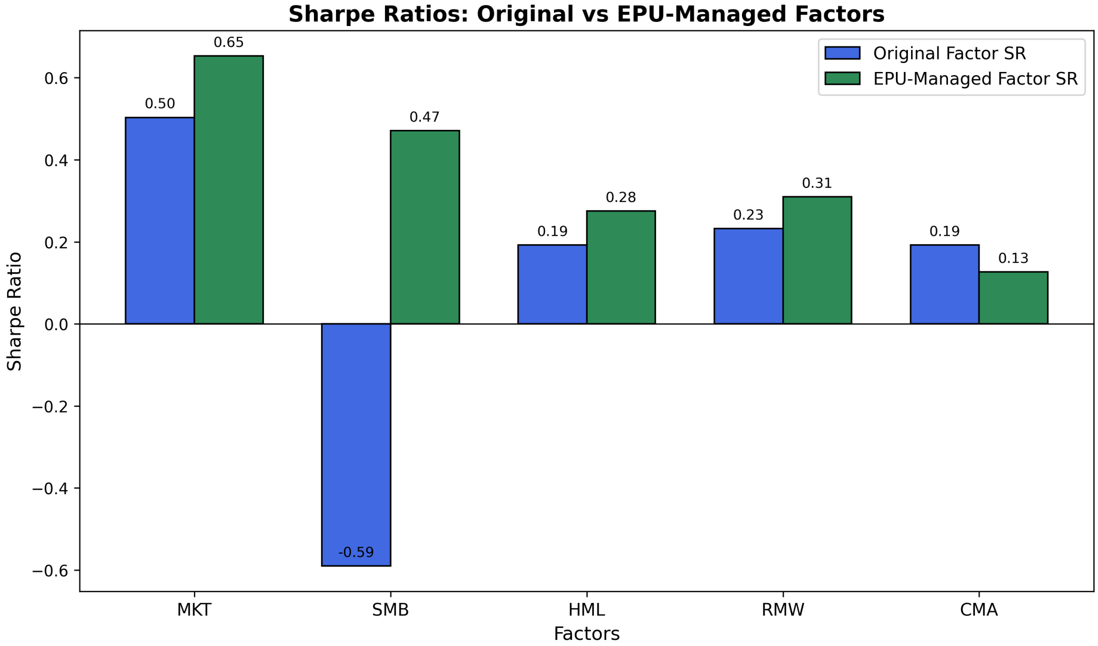

FIGURE 4.2: SR comparison

Sharpe Ratios improve from 0.50 in the original specification to 0.71 and 0.65 under volatility and EPU management, respectively. This supports the findings of Moreira and Muir (2017), and extends them by showing that macroeconomic state variables such as EPU can also serve as effective timing instruments.

The size factor (SMB) displays the most serious transformation: its original negative Sharpe Ratio of –0.59 becomes neutral when managed by volatility, and turns significantly positive under EPU-based management. This suggests that EPU helps recover predictive structure from a factor that appears unproductive in static form.

Both HML and RMW factors benefit from dynamic scaling, with Sharpe Ratios increasing from 0.19 to 0.30 (HML) and from 0.23 to 0.31 (RMW) under volatility management. EPU-based versions yield similarly strong performance, reaching 0.28 and 0.31, respectively. This indicates that both volatility and uncertainty measures provide useful information about time-varying risk-return trade-offs.

The CMA factor is the only case where volatility management leads to a deterioration in performance, with its Sharpe Ratio falling from 0.19 to –0.04. However, EPU-based scaling still yields an improved result of 0.13, suggesting that macro uncertainty may offer better signals for certain dimensions of asset pricing.

In summary, the evidence shows the value of incorporating dynamic scaling rules into factor investing frameworks. While volatility management remains effective in line with prior literature, EPU-based management appears to offer complementary and, in some cases, superior improvements—particularly for factors like SMB and CMA. These findings highlight the importance of conditioning factor exposure on both market risk and macroeconomic uncertainty to improve portfolio efficiency.

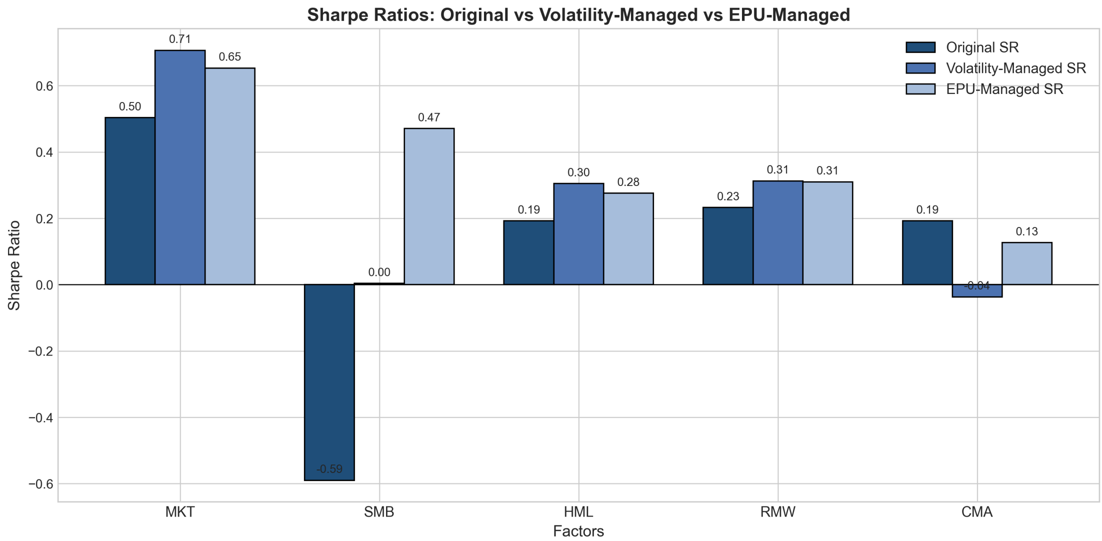

FIGURE 4.3: SR comparison

4.4 Statistical Significance

Table 4.1 presents the differences in Sharpe Ratios between volatility-managed and unmanaged portfolios, as well as between Economic Policy Uncertainty (EPU)-managed and unmanaged portfolios. The table reports both the Sharpe Ratios and the corresponding p-values of the Ledoit–Wolf test for the difference in Sharpe Ratios.

The results indicate that Sharpe Ratios differ meaningfully across management strategies. In particular, the Sharpe Ratio for the market factor improves under EPU-based management, and the difference is statistically significant at the 10% level. Similarly, the EPU-managed version of the SMB (Small Minus Big) factor shows a significant improvement, also at the 10% significance level. For the remaining factors—HML, RMW, and CMA—the differences in Sharpe Ratios under EPU management are not statistically significant.

Statistically significant improvements in Sharpe Ratios for volatility-managed portfolios are observed for the market and SMB factors, both at the 10% confidence level. For the other factors, the Sharpe Ratio differences are positive but not statistically distinguishable from zero.

Overall, the findings suggest that both volatility-based and EPU-based dynamic management can enhance risk-adjusted returns for certain factors, particularly the market and size factors, though the effects are not uniform across the entire factor spectrum.

TABLE 4.1: Sharpe Ratio Differences: EPU-Managed and Volatility-Managed vs. Original OOS

	MKT	SMB	HML	RMW	CMA
SR (EPU-Managed)	0.59	-2.31	0.28	0.02	-1.08
p-value	0.09	0.06	0.35	0.27	0.39
SR (Volatility-Managed)	1.69	1.90	0.93	1.11	-0.87
p-value	0.09	0.06	0.35	0.27	0.39

Chapter 5

Discussion

The findings of this study indicate that volatility-managed factor portfolios generally have better risk-adjusted tradeoff. This result aligns with the theoretical intuition that dynamic risk scaling can improve risk-adjusted performance by reducing exposure during high-risk periods.

In addition to volatility-based management, portfolios managed via Economic Policy Uncertainty (EPU) and sentiment indicators also demonstrate superior Sharpe Ratios compared to static exposures. The improvements are particularly pronounced and statistically significant for the Market and SMB (Small Minus Big) factors. For other factors—HML, RMW, and CMA—the differences in Sharpe Ratios, while directionally consistent, are not statistically significant at conventional levels.

Importantly, the results suggest that the performance of EPU-managed portfolios is comparable to that of volatility-managed portfolios. The similarity in outcomes implies that EPU may serve as an effective proxy for market risk or uncertainty. This opens the possibility of using macroeconomic uncertainty indicators, such as EPU, as practical substitutes for volatility in managing factor exposure—especially when volatility estimates are noisy or unavailable.

Chapter 6

Conclusion

In this study, I develop a strategy that exploits both news sentiment to time exposure to prominent asset pricing factors. The methodology begins with the construction of baseline factor portfolios, followed by the creation of their volatility-managed counterparts using inverse volatility scaling. I then form a mean-variance optimal combination of the unmanaged and volatility-managed factors and evaluate performance based on Sharpe Ratios.

A parallel approach is applied using sentiment-based management. Specifically, I scale each factor by a sentiment indicator—proxied by the Economic Policy Uncertainty (EPU) index—and construct a mean-variance combination of the original and sentiment-managed factor. Across both approaches, I find that dynamically managed portfolios—whether volatility- or sentiment-driven—consistently outperform their unmanaged equivalents in terms of Sharpe Ratios. This result is largely attributable to the ARCH effect, which implies that conditional volatility and sentiment can serve as effective timing signals.

For future research, I recommend addressing several limitations of the current study. First, incorporating transaction costs into the optimization process is crucial for evaluating real-world applicability. The Parametric Portfolio Policy framework offers mechanisms to account for such costs by recognizing offsetting trades across factor loadings. Second, it is important to reconstruct factor returns manually to reduce survivorship bias caused by dropping rows with missing or zero values. Finally, applying the model across different countries would help assess its robustness and mitigate potential sample selection bias.

Despite certain limitations, this research contributes meaningful insights. It demonstrates that both volatility-based and sentiment-based timing strategies can enhance factor portfolio performance. Furthermore, it underscores the potential of dynamic allocation frameworks in improving the out-of-sample efficiency of investment strategies, offering valuable implications for quantitative portfolio managers.

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