ADDING SENTIMENT TO MULTIFACTOR EQUITY STRATEGIES

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Summary

Sentiment in news and social media is increasingly seen as a valuable addition to more traditional investment signals and is gaining popularity in the investment community as a source of alternative data. The data can be used to seek additional return as well as limit the risk of investment portfolios.

In this paper, we explore sentiment in the framework of multifactor investment strategies. We investigate the relationships between sentiment-based and more traditional factor strategies and show that sentiment offers an additional signal that can contain information that is not incorporated in traditional investment factors.

We show that an equity investment strategy based solely on sentiment performs on par with a traditional multifactor model that incorporates several well-known factors such as size, growth, momentum and volatility. If sentiment is added to these factors, the strategy shows further additional gains in terms of return, without increasing risk.

A more detailed investigation of adding sentiment as a risk overlay - essentially avoiding stocks with declining sentiment - demonstrates that strategies' returns are enhanced if sentiment is used in an aggressive way to screen the stocks. Avoiding entire sectors with declining sentiment further improves performance.

Finally, we conclude that combining the use of sentiment in several ways - such as risk screening for stocks as well as for sectors and adding sentiment as a factor to multifactor strategies - achieves the greatest benefits in terms of portfolio performance. It can lead to over 4% yearly return enhancement, even in periods of bullish markets when beating the benchmark is particularly difficult.

1 Introduction

All quantitative investment strategies need two things: data and a model.

Regarding data, an important question is: what kind of data? Should the data be observable and available for the implementation of the investment strategy based on the model?

Technological innovation has hugely increased the volume and variety of available data over the past decade and this is likely to continue ever more rapidly. This does not necessarily mean traditional models lose their value. However, it does raise the question of how opportunities to apply new data should be incorporated in the investment process.

News is a well-known driver of security prices, but its effects have previously been difficult to quantify. This paper uses quantitative news characteristics from the Refinitiv News Analytics (RNA) database to address the issue.

News has an impact on security prices depending on its sentiment. Generally, when news regarding a stock becomes more and more positive, increasing its sentiment, more investors consider buying the stock, resulting in a positive impact on its price. The change of sentiment is the price driver, rather than the level of sentiment. In this paper, we use this characteristic of news – the change in sentiment – combined with other quantitative news characteristics to capture the influence of news on stock prices.

The paper compares an equity strategy based on a traditional multifactor model to variations that also include sentiment. We have chosen the Fama & French factor model as the traditional model for the research. The main question we answer is whether there is added value in including sentiment in existing investment models.

Sentiment data can be applied in many ways with different levels of sophistication. For this paper, we have chosen easy implementations of sentiment and easy investment strategies so that our conclusions apply in a general setting.

The applications of sentiment analyzed in this paper are:

- Sentiment as a separate investment factor
- Sentiment as a risk overlay for individual stocks
- Sentiment as a risk overlay for sectors
- Combinations of the above strategies

In the remainder of the paper, we will describe the data, the methodology and the sentiment-based investment strategies.

Retrospective and cross-sectional analysis for actionable signals

Use of speed versus use of speed and acceleration

The level of sentiment does not tell us much about the future price dynamics. It is the change of sentiment that potentially adds value of sentiments, captured by speed or acceleration (or both). In a cross-sectional approach, the change of sentiment of a stock is compared with that of other stocks. In a retrospective approach, a stock's sentiment change is compared with the stock's own previous sentiment changes. Naturally, the cross-sectional approach is more appropriate when the portfolio is to be fully invested, while retrospective analysis suits better when the investment decision is to either invest in a stock or to hold on to cash. The analysis in this paper is cross-sectional and the change of sentiment is captured by speed. Adding in retrospective analysis and/or sentiment acceleration is possible and is a fruitful direction for further research.

2 The setup

2.1 The data

The market data for this research is comprised of the stock prices of the S&P 500 index constituents over the period 2008 – 2018. The historical period for testing investment strategies starts January 18, 2010 and ends December 31, 2018, which equals 36 periods of 13 weeks.

The source of the sentiment data is the Refinitiv News Analytics (RNA) engine, which uses complex natural language processing algorithms to read and interpret (in real time) all news on the Reuters Newswire. Each news item is tagged in relation to a company or a commodity – currently 37,000 companies worldwide are incorporated into the engine, as well as 40 commodity classes.

For each news item, the algorithms return a wealth of quantitative characteristics. The most important is the sentiment score, the probability that a particular news item conveys a positive, negative or neutral outlook on the price of the asset relevant to the news item. The relevance score is also provided, indicating how relevant a particular news item is for the asset. Further, a variety of novelty indicators are provided, such as the number of similar news items identified before and after the news item that is scored for sentiment.

The outputs of the RNA engine are summarized below:

- Relevance: A score between 0 and 1 indicates the likelihood of a news item being relevant for a specific company or commodity.
- Sentiment Score: The likelihood that a particular news item conveys a positive, negative or neutral outlook on the price of the relevant asset.
- Novelty: The number of news items with similar content published previously. The database covers different time spans: 12 hours, 24 hours, three days, five days and one week.
- Volume: The ex-post calculated number of repetitions found after the first news item with a particular type of content has been released. For this indicator, time horizons cover: 12 hours, 24 hours, three days, five days and one week after publication of the first news item.

These quantitative inputs are processed according to the methodology described in Borovkova & Mahakena (2015), to obtain de-noised and aggregated investment signals. This methodology is currently used by Probability & Partners for creation of the so-called Probability Sentiment Indices (PSI). Note that the "raw" sentiment scores from the RNA engine can be very noisy, as media is not always in agreement about the role of specific events on a company's share price and also because NLP algorithms might have inherent errors in their interpretation. This may lead to noisy investment signals and high turnover of sentiment-based strategies. Therefore it is important to de-noise sentiment signals before using them in quant strategies, as we do with the PSI methodology.

All the data in our research (i.e., data needed to construct and select the factors for the factor model, the sentiment data and stock returns for performance calculation) are gathered on a weekly basis. Rolling two-year windows are used for model estimation. All monetary variables are denoted in USD.

The S&P 500 reinvested market index represents the market portfolio. In a real-world setting, it is likely that an investment strategy can have off-benchmark bets and will invest in stocks that are not constituents of the index. To avoid results being driven by these bets, such positions are not allowed and the actual historical compositions of the S&P 500 are used. This also avoids survivorship bias, which would be present in stock universes comprised only of currently existing stocks.

2.2 Traditional factor models in asset pricing

The methodology to construct the factor model follows a similar approach to the Fama and French framework (2015). This takes into account both the selection of factors and the creation of the factor values. Factors included in the analysis are **excess market return, size, value, momentum, low-volatility, and sentiment**. Applying a factor model does not come with a prescriptive method on how to construct an investment portfolio. We have chosen to employ the alpha momentum strategy from Hühn and Scholz (2018).

2.3 Portfolio construction

When defining a portfolio, several considerations are important. On the one hand, we should consider the consequences for the risk profile of the portfolio which are relevant for fair performance evaluation. On the other hand, we need to be able to attribute results to the performance drivers being tested. These considerations have led us to the following framework:

1. **Factor model portfolios:**
   a. Construct sub-portfolios on the sector level
   b. Equally weight the 10 best ranked stocks in the sector
   c. To reduce turnover, a portfolio constituent is only sold when its rank drops below 15
   d. Apply the same sector weights as in the S&P 500 index to combine sub-portfolios

2. **Sentiment as a risk overlay and to enhance upside potential:**
   a. Construct sub-portfolios on the sector level
   b. Exclude stocks with the lowest sentiment scores (in terms of weekly change in sentiment)
   c. Apply S&P stock weights and scale to 100%
   d. Overweight respectively underweight

3. **Combined use of sentiment:**
   a. Construct sub-portfolios on the sector level
   b. Exclude stocks with lowest sentiment scores
   c. Equally weight the 10 best ranked stocks in the sector
   d. Overweight respectively underweight

The choice to apply same sector weights as in the index serves the following purpose: warranting that the strategies' performance does not differ in the level of systemic risk when compared with the index. Secondly, value added by sentiment as a factor in a factor model can be distinguished from value added by sentiment as a performance driver when the latter is implemented by tilting sector weights.

2.4 Sentiment score generation

News items are published 24/7, also during weekends, holidays and outside exchanges' trading hours. As news appears continuously, it is important to calculate actionable sentiment-driven signals shortly before the intended moment of trading. This is valid for all the strategies that use sentiment, ranging from low to high trading frequency. In our research, the update frequency is weekly. We have chosen the moment just prior to the close of business on Mondays as the cutoff for the news feed.
This is also the moment of the sentiment calculation and trade execution.

2.4.1 Sentiment speed and acceleration

The stock-specific value of sentiment indicator (PSI) represents the net positive media sentiment for that particular stock. As we mentioned in the introduction, it is the change in sentiment that drives the stock price, rather than the level of sentiment. So, the actionable signals we designed in this study are based on the weekly changes of sentiment. Another quantity that can be considered is how fast sentiment is changing, the second order difference in sentiment:

Sentiment change (speed)	Sentimentt – Sentimentt-1
Sentiment acceleration	$[\text{Sentiment speed}]_{t}$ – $[\text{Sentiment speed}]_{tt-1}$

2.4.2 Actionable signals

The choice between the speed (i.e., change) and acceleration of sentiment as a signal in investment strategies depends on the role sentiment is to play in the investment process and on the type of investment product.

For example, when applied as a risk overlay, the *acceleration* towards more negative sentiment could be of high importance, while *speed* can serve as a factor in a factor model. Furthermore, a fully invested portfolio or an equity-or-cash strategy will also have different demands on sentiment. When the portfolio is going to be fully invested, a stock's sentiment (speed and/or acceleration) relative to sentiment of other stocks is important. The stock's sentiment relative to its own prior values would be the most discriminating factor in an equity-or-cash strategy. Also, quite intuitive is that declining sentiment is a valuable signal when short positions are allowed.

As this paper intends to highlight three different applications of sentiment, we believe our message will best be delivered if things are kept simple. So, for the purposes of the paper, we will be only applying weekly sentiment change (see below). For a specific investor, investment process or product, it is possible that a more involved sentiment model would add more value.

Sentiment application

Factor in factor model	Change of sentiment per stock
Risk overlay/filter	Quartile ranking of stocks according to sentiment change
Upside potential enhancement	Sentiment change aggregated to sector level for sector tilts

3 Application of sentiment as a factor in a factor model

In this section, we describe how we construct and apply factor models. We construct two types of factor models: without and with sentiment as a factor. These are referred to as "standard factor model" and "standard + sentiment factor model."

3.1 The factor model

As in traditional factor model literature, we explain the excess return of a stock using well-known factors such as the market, size, value, momentum, low-volatility factors and the new sentiment factor. Previous literature has extensively examined the relationship between stock returns and these factors, as well as interrelationships between these factors. However, research on including sentiment in factor models is scarce. So here we include sentiment delta (i.e., change) as a factor in a multi-factor model.

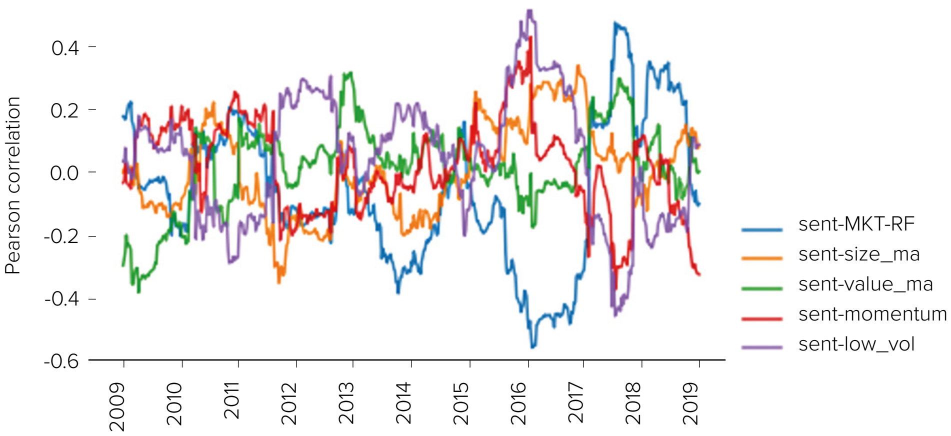
Table 1 gives the correlations between the factors for U.S. stocks. Figure 1 provides an illustration of the 1 year rolling correlation between sentiment and other factors. There seems to be no significant linear relationship between sentiment delta and the other factors.

Table 1. Factor correlations

	Correlation matrix factors					
	Mkt-rf	Size	Value	Momentum	Low volatility	Sentiment
Mkt-rf	1.00	0.24	0.29	-0.25	-0.78	-0.09
Size	0.24	1.00	0.17	-0.12	-0.27	-0.01
Value	0.29	0.17	1.00	-0.15	-0.36	-0.08
Momentum	-0.25	-0.12	-0.15	1.00	0.42	0.02
Low volatility	-0.78	-0.27	-0.36	0.42	1.00	0.09
Sentiment	-0.08	-0.01	-0.08	0.02	0.09	1.00

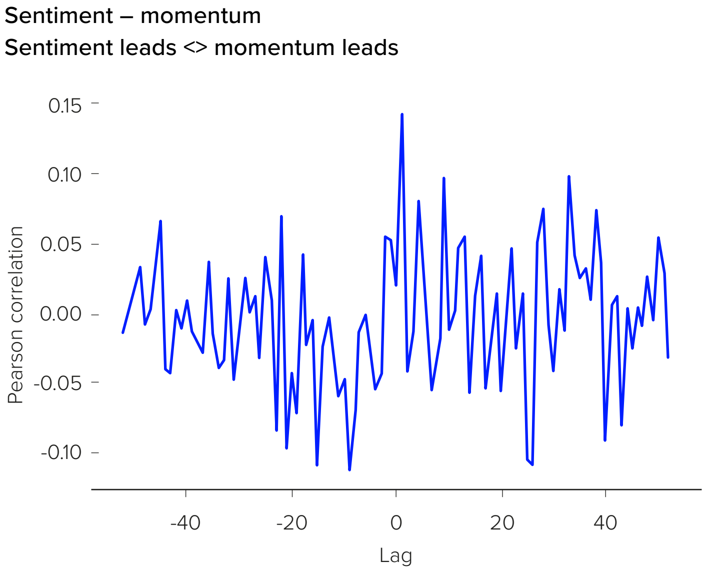
Figure 1. One-year rolling factor correlations visualized

Rolling one-year correlation of sentiment with other factors



We also looked at the time lagged cross correlations (TLCC) between sentiment and other factors. TLCC can indicate causality between two signals. Figure 2 illustrates the TLCC between sentiment and momentum, with different time shifts (in weeks). The peak occurs at lag of -1, indicating that the two signals are most synchronized at one week and that sentiment is the leading indicator.

Figure 2. Sentiment vs. momentum



We regress weekly excess returns for each of the historical S&P 500 constituents on the factor returns. The regression utilizes the two-year look-back window of historical data to estimate the model coefficients. This is done with quarterly frequencies. After each regression is completed, the regression alphas are ranked to construct the portfolio for the next 13-week period. At the end of this 13-week holding period, the regression and construction process gets repeated. This is the essence of the alpha-momentum multifactor strategy.

The standard factor model contains the factors market, size, value, momentum and low volatility:

$$R_{Stock} = \alpha + \beta_1 (R_{Market} - R_f) + \beta_2\, Size + \beta_3\, Value + \beta_4\, Mom + \beta_5\, lowVol.$$

The other model includes sentiment as an additional factor:

$$R_{Stock} = \alpha + \beta_1 (R_{Market} - R_f) + \beta_2\, Size + \beta_3\, Value + \beta_4\, Mom + \beta_5\, lowVol + \beta_6\, Sentiment.$$

3.2 Factor model results

3.2.1 Operational process

The factor model is estimated quarterly, using weekly data over a rolling time-window of two years, for each constituent of the S&P 500. Per sector, the alphas of the stocks are ranked to select the top 10 stocks to form an equally weighted sub-portfolio. A turnover measure is in place that allows formerly selected stocks to drop to rank 15 before actually being dropped. The S&P 500 consists of 11 sectors. Therefore, 11 sub-portfolios are weighted using the actual S&P 500 sector weights to construct the portfolio resulting from factor model analysis.

The process is executed for the factor models: "standard," "standard + sentiment" and "sentiment only." The performance of the three associated portfolios is measured weekly on a total return basis (price return with dividend reinvested).

3.2.2 Performance

The performance of the factor models is measured by the investment returns resulting from portfolios built on the factor model outputs. Table 2 shows that the annual return of the standard factor model exceeds the return of the reinvested S&P 500 index by 2.58%. The volatility of the equally weighted 110-stocks portfolios is some 1.8% higher than the volatility of the market-weighted index of 500 stocks. The portfolios track the index by a little more than 4%.

Table 2. Factor model-based investment results

	Return	Volatility	Tracking error	Information ratio	Sharpe ratio	Turnover
S&P 500	11.21%	15.55%			0.70	0%
Standard factor model	13.79%	17.32%	4.27%	0.61	0.78	48.50%
Standard model + sentiment	14.28%	17.41%	4.23%	0.73	0.80	50.16%
Sentiment-only factor model	13.46%	17.09%	4.54%	0.49	0.77	50.98%

Annualized over the period 2010-2018
Turnover is measured by buys and sells

Evaluation of performance is made by using the Sharpe Ratio (SR) and Information Ratio (IR). Both calculate excess return per unit of risk. The difference between these measures is in the framework applied. The SR applies an absolute framework, where the excess return is measured as the return above the risk-free rate and risk is measured as the standard deviation of the weekly returns. The IR defines excess return as the outperformance above the index and measures risk as the volatility of the weekly excess returns (relative framework). The values of SR and IR indicate that the factor model-based portfolios add additional return in the range of 0.6% to 0.8% per unit of 1% risk. Given the length of period over which this is achieved, nine years, these outcomes are highly significant.

Of particular interest is the added value when sentiment is one of the factors. The comparison between the standard factor model and the standard model with sentiment shows an additional annual return of 0.5%, while the risk characteristics (volatility and tracking error) are not materially different. The IR is raised by 0.12 over a period of nine years.

We also constructed portfolios on the basis of a factor model that has only the market return and sentiment as factors. When compared to the standard factor model, we see that it adds the same amount of value (over the benchmark) as the full multifactor model.

Turnover of the portfolio when sentiment is added as one of the factors is slightly higher (by approx. 1.5%), but similar to the turnover of the factor portfolio (all turnover figures are in line with industry literature, see e.g., Li and Shim (2019)). This is a general observation: addition of sentiment results in a slightly higher turnover, but not significantly so. This is the result of using filtered sentiment signal, which is less noisy than "raw" sentiment (and which would lead to a higher turnover).

Another angle to evaluate the value added of the "standard + sentiment model" is to apply the relative framework such that the standard model plays the role of the index. Table 3 shows that the factor model with sentiment tracks the model without sentiment quite closely (tracking error of 1.14%), while generating an IR of 0.43. This means 43 basis points of additional return annually over a period of nine years for each 1% of tracking error. So, sentiment as an additional factor in a factor model adds significant value.

Table 3. Performance factor model with sentiment vs. factor model without sentiment

	Return	Volatility	Tracking error	Information ratio
Standard model + sentiment	13.79%	17.32%		
Sentiment-only factor model	14.28%	17.41%	1.14%	0.43

4 Sentiment as a risk overlay and as a performance driver

An investment strategy can be successful in many ways: outperformance can be measured in return, risk or in a combination of both. In this section, we describe two categories of strategies that can be labeled as “avoiding losers” and “picking winners.” Both strategies have the potential to enhance return, while the “avoiding losers” strategy can also help with avoiding losses.

Sentiment is used on the stock level within sectors to avoid stocks with the most unattractive outlook. This is called risk overlay and its exact implementation of it is explained in 4.1. Improving the upside is implemented on the sector level by over-respectively underweighting sectors that are attractive (respectively unattractive) according to sentiment which is described in 4.2. Both effects are combined in one final strategy that is described in 4.3.

4.1 Risk overlay:

The difference between picking winners and avoiding losers on the stock level is in some respect semantic if short positions are allowed. However, if the strategy allows only for long positions, then avoiding losers can make a difference in terms of risk. So, the essence of our sentiment-based risk overlay is avoiding a certain percentage of stocks that score lowest in terms of weekly change in sentiment. In the scenario “subtle,” the 10% of stocks with lowest sentiment change (i.e., greatest sentiment decline) are eliminated leaving 90% of the stocks present in the portfolio. In the scenarios of “medium” and “aggressive”, 30% and 50% respectively of the stocks are eliminated. Again, a sector bias is avoided by implementation per sector as described above. The stocks that remain are weighted according to their weight in the S&P 500 index, rescaled to add up to 100%.

4.2 Performance driver: sector rotation

The second application of sentiment is sector rotation: over and underweighting sectors on the basis of sector-level sentiment. Weekly sentiment changes are aggregated per sector by using S&P index weights and rescaling. This results in sector sentiment changes. Then we overweigh the top five (in terms of sentiment) of the 11 sectors in the S&P index, while underweighting the bottom five. Scenarios applied are again: subtle, medium and aggressive, whereby we overweigh "good" sectors by 10%, 30% or 50% respectively. Note that, if sector rotation is combined with risk overlay, then the above only applies to those stocks that are not excluded by the risk overlay.

4.3 Results

The combined risk overlay and sector rotation strategy potentially rebalances the portfolio on a weekly basis. The combinations of subtle, medium and aggressive sentiment application for both risk overlay and sector rotation give rise to nine strategies in total. The performance results of all these strategies are given in Table 4.

Table 4. Sentiment as risk overlay and for sector rotation

			Return	Volatility	Tracking error	Information ratio	Sharpe ratio
	S&P 500		11.21%	15.55%			0.70
	Screening	Sector rotation					
A	Subtle	Subtle	11.65%	20.10%	0.94%	0.47	0.56
B	Subtle	Medium	12.11%	20.63%	2.35%	0.39	0.57
C	Subtle	Aggressive	12.56%	21.26%	3.83%	0.35	0.57
D	Medium	Subtle	11.58%	20.29%	1.39%	0.27	0.55
E	Medium	Medium	12.39%	20.74%	2.73%	0.43	0.58
F	Medium	Aggressive	13.18%	21.28%	4.26%	0.46	0.60
G	Aggressive	Subtle	12.46%	20.68%	1.98%	0.63	0.59
H	Aggressive	Medium	13.09%	21.06%	3.16%	0.60	0.60
I	Aggressive	Aggressive	13.70%	21.57%	4.65%	0.54	0.62

Relative risk is more impacted by sector rotation than by risk overlay, given 3.83% of tracking error of "subtle and aggressive" (scenario C) compared to 1.98% of "aggressive and subtle" (scenario G). Value added per unit of relative risk IR is generally attractive for all strategies. The absolute return is highest when both applications of sentiment are the most aggressive (scenario I). The strategy of scenario I adds 2.49% per annum to the return of the S&P 500. The highest IR, however, results from scenario G: aggressive risk overlay (ignoring 50% of the stocks per sector with the lowest sentiment speed) and subtle sector rotation (giving only 10% of additional weight to sectors with highest speed combined with underweighting low-speed sectors).

5 Three applications of sentiment combined

Previous chapters applied sentiment three-fold. In Chapter 3, sentiment was used as an additional factor in a factor model, while Chapter 4 applied sentiment on its own for screening stocks and for sector rotation.

In this chapter, the three applications are combined. For sub-sector portfolio construction, the method of equally weighted top-10 stocks is used as a basis. The factor model alphas are leading and the factor model is still estimated quarterly. The risk overlay is added by screening for those stocks in the bottom section on sentiment speed ranking. This is done on a weekly basis. Sector rotation is also implemented on a weekly basis by applying the weekly sector weights that resulted from Chapter 4. Risk overlay and sector rotation are tested for subtle, medium and aggressive variations giving rise again to nine scenarios. Table 6 presents the results.

Note that the general level of tracking error in Table 5 is higher than in Table 4. This is due to the difference in portfolio construction: keeping most of the stocks according to their index weight (Chapter 4) versus top-10 equally weighted sector sub-portfolios (Chapters 3 and 5).

Table 5. Three applications of sentiment combined

			Return	Volatility	Tracking error	Information ratio	Sharpe ratio
	S&P 500		11.21%	15.55%			0.70
	Screening	Sector rotation					
J	Subtle	Subtle	14.45%	17.38%	4.45%	0.73	0.81
K	Subtle	Medium	14.57%	17.40%	4.93%	0.68	0.82
L	Subtle	Aggressive	14.66%	17.58%	5.90%	0.58	0.81
M	Medium	Subtle	14.51%	17.41%	3.80%	0.87	0.81
N	Medium	Medium	14.94%	17.57%	4.42%	0.84	0.83
O	Medium	Aggressive	15.34%	17.89%	5.55%	0.74	0.84
P	Aggressive	Subtle	14.78%	17.45%	3.71%	0.96	0.83
Q	Aggressive	Medium	14.92%	17.71%	4.39%	0.84	0.82
R	Aggressive	Aggressive	15.03%	18.11%	5.82%	0.66	0.81

Most important is the level of return. Roughly speaking, the values added above the index from a factor model (2% from Chapter 3) and from sentiment-only (2% from Chapter 4) can be added. The values added are quite independent and work together in a combined strategy.

Scenarios J, M and P are the subtle sector rotation scenarios. The screening aggressiveness increases from J to P. It is striking that tracking errors become smaller. All scenarios have screened equally weighted top-10 sector sub-portfolios. Therefore, it is not stock weights getting closer to their actual S&P 500 weights. It is the risk overlay at work. Banning high alpha stocks that score low on sentiment speed reduces spikes in weekly excess return. As a result, the return per unit of relative risk goes up and reaches 0.96 for scenario P. Increase of return is also a factor in the higher IR, but of less importance.

Quite intuitively, scenario I, aggressive on both risk overlay and sector rotation, produces the highest absolute return. Absolute and relative risk-adjusted return measures, however, are better with primarily smaller sector bets.

6 Concluding remarks and further work

The aim of quantitative investment processes is to select and utilize various available data sources, especially those that contain new information that is not yet incorporated in traditional investment factors. Sentiment is one such alternative data source that is currently at the forefront of quant investors' attention. It has the ability to capture, in a timely fashion, many aspects of a company that drive its stock price.

The aim of the paper was to show the added value of sentiment within the traditional multifactor investment process. We used sentiment in several ways: in the context of a factor model, by sentiment-only based risk strategy of "avoiding losers" and "picking winners" and by combining these approaches. We deliberately chose relatively straightforward strategies for reasons of robustness and ease of understanding. Our suggested strategies are robust, in the sense that their added value is due to the inclusion of sentiment data and not due to additional model complexity. Our work should be seen as examples of practical use of sentiment in the investment process, although quant investment specialists would likely develop their own (possibly more complex) investment models.

We measure the added value of sentiment-based strategies as an excess return above the S&P 500 reinvested index over the period 2010-2018. This added value is statistically and economically significant for all considered applications of sentiment. In a factor model, most of the return above the index (2.58%) comes from the traditional factor model. Sentiment adds 0.49% per annum and increases the IR by 0.12. The length of period of nine years makes these results significant.

Sentiment by itself, used for "avoiding losers" and sector-level "picking winners" strategy adds up to 2% per annum. When this strategy is combined with the "factor model with sentiment," the combined added value is only modestly lower than the sum of the individual strategies' added values, showing relative independence of the various positive effects of sentiment. The IR of the combined strategy is up to 0.96, adding 0.96% per annum to the reinvested S&P 500 index per 1% of tracking error over a period of nine years. Note, these results emerge in the restricted set-up of no off-benchmark positions.

The application of sentiment in the investment world is still quite new. Several categories of further research can be identified, such as:

- The sentiment change, used in this paper, can be enhanced by adding the "sentiment acceleration," i.e., how quickly sentiment is changing for a particular stock or a sector
- Sentiment can be applied to investing in other markets (such as commodities and bonds) and can be related to other active investment decisions, such as region tilting

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