Does Investing with Collective Financial Intelligence Generate Alpha?

Master Thesis in Banking and Finance

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Abstract

The Swiss FinTech Start-up Sentifi uses a combination of supervised and unsupervised machine learning to score the financial relevance of content published by people on social media and in blogs. This thesis analyses this unique data. The author finds that the sentiment data provides explanatory power for stock returns. Several portfolios built with different strategies based on the Sentiment-Score and Attention-Buzz performed better than their respective benchmark in a backtest over the period from 05 March 2018 to 14 June 2019. Furthermore, a long/short strategy generated a positive and significant alpha between 0.1% and 0.3% over the observed period.

Keywords: Crowd intelligence, stock returns, abnormal returns

JEL Classification: D14, G11, G23, M13

Executive Summary

Introduction

Over the past decade, the influence of social media has increased in many areas of our lives. Also in the financial world, social media has left its mark. More and more news is produced and consumed on such portals. Therefore, in recent years, the share of traditional financial information has been steadily declining, and the sources and volumes of alternative financial information are continuing to grow. Since news containing financial information moves the market, this alternative financial information must not be neglected. Therefore, news analytics plays a key role in financial markets. According to a growing body of research literature, news and media influence the investors sentiment and hence the stock prices (Tetlock (2007), Mitra and Mitra (2011), Leinweber and Sisk (2011), Barber and Odean (2011)). But since financial news from new sources is often in an unstructured and textual form, it is hard to quantify. Therefore, there is a need for effective models which are able to incorporate sentiment data.

The Swiss FinTech start-up Sentifi, which is short for "Sentiments in Finance", helps to meet this need. Sentifi uses a combination of supervised an unsupervised machine learning to score the financial relevance of the content published by people on social media and blogs. The "Sentifi Engine" helps to extract and quantify sentiment data so that it can be easily applied to the investment decision-making process. The task of this thesis is to analyse the sentiment data provided by Sentifi and to check, whether it is possible to generate an excess return, also referred to as alpha by Jensen (1967). The research question, whether investing with collective financial intelligence does generate alpha, will be answered by developing and testing different strategies based on the sentiment data provided by Sentifi.

The question of whether it is possible to generate alpha with the help of sentiment data, both from traditional and new sources, has been a concern for scientists for a long time. While the followers of Fama (1970)'s efficient market hypothesis argue that capital markets are efficient (at least in the semi-strong form) and therefore, that stock prices fully reflect past stock prices and all publicly available information, various studies have shown that a sentiment-based trading strategy can achieve a certain excess return (e.g. Breitmayer, Pelster, and Massari (2016), Hafez (2011), Tetlock (2007), Lugmayr (2013), Leinweber and Sisk (2011)). The author states the hypothesis that it is possible to generate alpha with Sentifi's unique data set. Thus, he also implies the hypothesis that the semi-strong form of the efficient market hypothesis is not given. By exploiting a very unique and new data set provided by Sentifi, this thesis contributes to the research on social media, crowd investing, sentiment analysis and stock markets, significantly differing from the existing literature.

Method

The data sample consists of all stocks which were listed in the S&P 500 index, the Stoxx Europe 600 index and the Swiss Performance index as of 01.12.2017. The sample period is from 01.12.2017 until 15.06.2019, which is the maximum period Sentifi can extract at the moment. This amounts to a total of 1'284 shares and a total of 738'468 daily Sentiment-Scores considered in the sample.

In order to test whether the data supplied by Sentifi can generate alpha, the author develops various strategies in a first step. These strategies are based on the Sentiment-Score - which indicates the crowd sentiment towards an asset - and the Attention-Buzz - a measure that indicates a company's above-average attention. These strategies are then tested in the form of a backtest over the observation period. Due to the short observation period, it is not possible to divide the data set by date. In order to still perform an out of sample test and thus minimize the problem of over-fitting, the data set is divided, and a sub-sample is created for each index. The strategies are only developed on the S&P 500 subset and afterwards applied to the other two subsets. In this approach - which could be called a "cross-section out of sample test" - the S&P 500 subset serves as the training set and the other two subsets serve as the test sets.

Since a backtest has only limited validity, the author examines in a further step the achieved portfolio returns with the concept of abnormal returns. The concept of abnormal returns is borrowed from the event study technique and makes it possible to isolate the effect of stock-specific reaction to the sentiment data (Hafez (2009)). To test whether a strategy generates excess return, time-series regressions are being run on a model consisting of the five Fama and French (2015) factors and the momentum factor from Carhart (1997). If the exposure to the respective factors captures all variation in expected returns, the intercept α_i would be zero. If there is excess return, the intercept is positive. To test the robustness of this model, further models were applied.

Results

The backtests carried out show that all the strategies developed beat the respective benchmark over the observation period. The executed time-series regressions prove that it is possible to generate an abnormal return with Sentifi's sentiment data, which doesn't just reflect more loadings on the economic risk factors. A long/short strategy based on the Sentifi Sentiment-Score and Attention-Buzz data generated a positive and significant alpha on the S&P 500, the Stoxx Europe 600 and the SPI Index between 0.1% (SPI & Stoxx Europe 600) and 0.3% (S&P 500) over the observed period. Furthermore, other strategies have also generated a positively significant alpha on various indices. These results confirm the hypothesis initially formulated and further imply that the semi-strong form of the efficient market hypothesis is not given.

Evaluation

This study presents interesting findings regarding the possibilities provided by the sentiment data of Sentifi. However, these results must take into account that the study deals with major and minor shortfalls. In particular, the transaction costs not taken into account, and the short observation period must be mentioned here. The transaction costs incurred would reduce the alpha generated to a large extent or eliminate it completely. Additionally, due to the short observation period, it is not possible to estimate how the strategies will perform in different economic cycles.

This and the great possibilities that the Sentifi Engine offers and will continue to offer in the future, however, provide the opportunity for further studies in this field. Especially the Sentifi event recognition tool and the combination of sentiment data and other trading relevant information, such as volatility analytics, allow the development and testing of additional exciting strategies that are left to further research.

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Zurich, May 23, 2019

Issued assignment for the master thesis

Dear Mr Helbling

I was delighted to hear about your interest to write a master thesis under my supervision. I hereby hand you the following assignment:

Title:
Does Investing with Collective Financial Intelligence generate Alpha?

Background:
News plays a key role in financial markets. Due to a change in the way people consume and produce news, traditional financial information covers just about 10% of the total available financial information. The sources and volumes of alternative financial information continue to grow. New technologies enable automatic or semi-automatic news collection, extraction, aggregation and categorization.

Objectives:
In an introductory part, this thesis provides a concise overview over existing approaches to generate alpha based on alternative financial information.

The main objective of this thesis is to check, whether it is possible to generate abnormal returns by applying an investment strategy based on sentiment data from news article, blog article and twitter posts. The strategy is based on the dataset provided by Sentifi, which contains alternative data about the stocks included in the S&P 500 and in the EURO STOXX 50 from January 2018 until Mai 2019. The methods used shall be described in detail and the statistical commands (from R) used to implement those methods are an integral part of the thesis.

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For any further questions, please contact Benjamin Wilding, institute for Banking and Finance, email: benjamin.wilding@bf.uzh.ch

I wish you good luck and success!

Kind regards

Markus Leippold
Professor of Financial Engineering
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List of Abbreviations

CAPM	Capital Asset Pricing Model
CMA	Conservative minus aggressive
HML	High minus low
Mkt	Marked return
MktRF	Market risk premium
Mom	Momentum
OOS	out of sample
RF	risk free rate
RMW	Robust minus weak
SMB	Small minus big
SPI	Swiss Performance Index

1 Introduction

Over the past decade, the influence of social media has increased in many areas of our lives. Also in the financial world, social media has left its mark. More and more news is produced and consumed on such portals. Therefore, in recent years, the share of traditional financial information has been steadily declining, and the sources and volumes of alternative financial information are continuing to grow. Since news containing financial information moves the market, this alternative financial information must not be neglected. Therefore, news analytics plays a key role in financial markets. According to a growing body of research literature, news and media influence the investors sentiment and hence the stock prices (Tetlock (2007), Mitra and Mitra (2011), Leinweber and Sisk (2011), Barber and Odean (2011)). But since financial news from new sources is often in an unstructured and textual form, it is hard to quantify. Therefore, there is a need for effective models which are able to incorporate sentiment data.

The Swiss FinTech start-up Sentifi, which is short for "Sentiments in Finance", helps to meet this need. Sentifi uses a combination of supervised an unsupervised machine learning to score the financial relevance of the content published by people on social media and blogs. The "Sentifi Engine" helps to extract and quantify sentiment data so that it can be easily applied to the investment decision-making process. The task of this thesis is to analyse the sentiment data provided by Sentifi and to check, whether it is possible to generate an excess return, also referred to as alpha by Jensen (1967). The research question, whether investing with collective financial intelligence does generate alpha, will be answered by developing and testing different strategies based on the sentiment data provided by Sentifi.

The question of whether it is possible to generate alpha with the help of sentiment data, both from traditional and new sources, has been a concern for scientists for a long time. While the followers of Fama (1970)'s efficient market hypothesis argue that capital markets are efficient (at least in the semi-strong form) and therefore, that stock prices fully reflect past stock prices and all publicly available information, various studies have shown that a sentiment-based trading strategy can achieve a certain excess return (e.g. Breitmayer, Pelster, and Massari (2016), Hafez (2011), Tetlock (2007), Lugmayr (2013), Leinweber and Sisk (2011)). The author states the hypothesis that it is possible to generate alpha with Sentifi's unique data set. Thus, he also implies the hypothesis that the semi-strong form of the efficient market hypothesis is not given. By exploiting a very unique and new data set provided by Sentifi, this thesis contributes to the research on social media, crowd investing, sentiment analysis and stock markets, significantly differing from existing literature.

The remainder of the thesis is organized as follows. After this introduction, the second section sums up the existing literature. Section three introduces the novel dataset used in the empirical study as well as the company Sentifi. Section four consists of an introduction to the theory of backtesting as well as an introduction to the theory of abnormal returns. Furthermore, trading strategies are developed and tested. The obtained results are presented in section five, alongside shortfalls and further research ideas. Finally, section six concludes the thesis.

2 Literature Review

Since Jensen (1967) defined the term "alpha", generating it is something like the holy grail of investing and therefore it is a major topic in research. This section provides a brief overview of the existing literature related to this thesis.

According to the semi-strong form of the efficient market hypothesis stated by Fama (1970), stock prices follow a random walk and fully reflect past stock prices and all publicly available information. Therefore, neither fundamental nor technical analysis would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks with comparable risk (Malkiel (2003)). The foundations of the efficient market theory rest on three main arguments. First, investors are rational. Second, if some investors are not rational, their trades are random, hence cancel each other out and ultimately have no effect on prices. Finally, rational arbitrageurs will meet irrational investors in the market, and any influence they have on the market will be eliminated (Lawrence, McCabe, and Prakash (2007)). Until the beginning of the twenty-first century, this theory had a dominant position (Malkiel (2003)). Since then, however, the intellectual dominance of the efficient market hypothesis had become more and more controversial. New approaches with psychological and behavioural elements as well as new technologies emerged and contributed to the belief that future stock prices are somewhat predictable based on certain fundamental valuation metrics (Malkiel (2003)). Mainly the new theory of behavioural finance has emerged with an alternative view of financial markets. It no longer expects financial markets to be efficient and it allows that significant deviations can persist for a long period of time while it rests on the foundation of limited arbitrage and investor sentiment (Lawrence, McCabe, and Prakash (2007)).

In this process, news as a key source of investment information plays an important role, since it is broadly accepted that financial news moves stock prices (Hafez (2011)). As the volume and sources of news are growing rapidly, news analytics in finance is getting more and more important (Mitra and Mitra (2011)). Hafez (2011) states that news not only moves stock prices through a direct impact on a company's expected future cash flow or the discount factor that one uses but also through a more behavioural or sentiment-based mechanism. According to Hafez (2009), market sentiment is the favourable or unfavourable mood among investors and analysts at a given point in time regarding future market price developments of individual companies or the overall market. DeLong, Shleifer, Summers, and Waldmann (1990) defined investor sentiment as a belief about future cash flows and investment risk that is not justified by the facts at hand.

As a consequence, many researchers have developed trading strategies to see if it is possible to generate excess returns or predict stock prices based on these market or investment sentiments. Kim (2018) developed a momentum strategy that relies on the argument that sentiment affects momentum profits. The idea behind this sentiment based momentum strategy is to invest more while optimistic sentiment is present, and less while pessimistic sentiments are dominating

(Kim (2018)). By applying this strategy to a portfolio of U.S. individual stocks, Kim (2018) finds that sentiment based strategy significantly outperforms the conventional momentum strategy.

Tetlock (2007) constructed a measure of media content that appears to correspond to negative investor sentiment. The result is that high values of media pessimism cause downward pressure on market prices and unusually high or low values of pessimism lead to high market trading volume (Tetlock (2007)). Given this, Tetlock (2007) created a sentiment-based trading strategy using negative words that yield a risk-adjusted excess return of 7.3% per year.

The main finding of Baker and Wurgler (2006) is that investor sentiment affects the cross-section of future stock returns, in such a way that shares of companies that are younger, smaller, more volatile, unprofitable, non-dividend paying, distressed or with extreme growth potential are less sensitive to sentiment. And vice versa stocks with bond-like attributes will be less driven by sentiment (Baker and Wurgler (2007)). Furthermore, several firm characteristics that do not have unconditional predictive power hide strong conditional patterns that become visible only after conditioning on sentiment (Baker and Wurgler (2006)). In addition, Baker and Wurgler (2007) clarify that the question no longer is, whether investor sentiment affects stock prices, but rather how to measure and quantify investor sentiments.

While the sentiment data in the above-mentioned studies originate from traditional financial data such as newspaper, sentiment indices or simple questionnaires, new technologies have created a multitude of alternative sentiment data that could not be used in the past. New technologies enable automatic or semi-automatic news collection, extraction, aggregation, and categorization of quantitative and qualitative alternative financial data (Mitra and Mitra (2011)). This data originates from blogs, wikis, and most importantly from social media and therefore, might act as a market or investor sentiment indicator due to the collaborative knowledge shared on such platforms (Lugmayr (2013)). Researchers take advantage of new and improved data to quantify investor sentiment and remeasure whether sentiment can predict stock prices or not.

Bollen, Mao, and Zeng (2011) investigate whether investor sentiment derived from large scale Twitter feeds are correlated to the value of Dow Jones Industrial Average over time. Brown (2012) had a similar idea and studied whether there is a correlation between Twitter and the stock market by checking sentiment, message volume, price movement and stock volume and additionally, the effect that a Twitter user's reputation may have on sentiment and the stock market. Bollen, Mao, and Zeng (2011)'s results indicate that the accuracy of stock price predictions can be significantly improved by including some public mood dimensions. Their study leads to the conclusion that Twitter feeds can predict the daily up and down changes in the closing values of the Dow Jones with an accuracy of 86.7% (Bollen, Mao, and Zeng (2011)). However, this high accuracy has to be enjoyed with caution since this analysis does not acknowledge several important factors (Bollen, Mao, and Zeng (2011)). In contradiction, Lugmayr (2013), who has researched whether social media, in general, can predict stock prices, concludes that it is not perfectly possible and views social media sentiment analyses just as an additional tool to

assist investors in their decision process.
Oh and Sheng (2011) analysed investor sentiment expressed in stock microblog postings from "Stockwits.com" and stated the hypothesis, that the predictive performance for postings of bearish sentiment is higher than that of bullish sentiment. Their empirical analysis supports this hypothesis which supports the fact, that pessimistic information has got more attention then optimistic information (Oh and Sheng (2011)).

Leinweber and Sisk (2011) generate investment signals by measuring the relevance, sentiment, novelty, and volume of news. They then process event studies on U.S. equities and show that there is exploitable alpha in news (Leinweber and Sisk (2011)).

Since gathering all the stock related news and posts on social media is quite challenging and expert knowledge in programming, machine learning and artificial intelligence is needed to process the textual input of news stories to determine quantitative sentiment scores, professional data providers developed methodologies and technologies to extract the wisdom of crowds (Mitra and Mitra (2011)). Hereby the wisdom of crowd means, that many users reach better decisions than an individual (Breitmayer, Pelster, and Massari (2016)). These data providers make life a lot easier for researchers, and some interesting work from such collaboration has already been published. For example, Breitmayer, Pelster, and Massari (2016) analyse data from Sharewise, a platform where its users can observe the results of the shared stock price assessment in one final quantified target price and get a simple buy or sell recommendation. This has the big advantage that users don't face the risk of misinterpreting verbalized opinions (Breitmayer, Pelster, and Massari (2016)). With this data, they empirically and theoretically examine whether the final target price provides explanatory power for future stock returns (Breitmayer, Pelster, and Massari (2016)). They find that a portfolio based on social media opinions generated an excess return of 3.4% between August 2007 and July 2015 and therefore provide evidence that standardized crowd opinions contain valuable information for predicting stock returns (Breitmayer, Pelster, and Massari (2016)).
Another platform that provides sentiment analytics is RavenPack. Hafez (2011) considered RavenPacks Event Sentiment Score, which indicates how event categories are typically rated by financial experts. Furthermore, he tests market-level sentiment strategies as well as industry-level sentiment strategies and finds that it is possible to generate an excess return with both strategies (Hafez (2011)).

The contribution of this thesis is the following: It extends the research on social media, crowd investing, sentiment analysis and stock markets and significantly differs from the existing literature, as the author works with unique and new data from Sentifi, a Swiss FinTech start-up, which uses a combination of supervised and unsupervised machine learning to score the financial relevance of the content published by people on social media, blogs and in news.
More about Sentifi and what distinguishes and separates the new data from other providers is explained in the following chapter.

3 Data

This section introduces the novel and unique dataset used in this empirical study as well as the company Sentifi, which collects, processes and provides the dataset. Furthermore, the author reports descriptive statistics and present his choice for the main dependent and independent variables.

3.1 Sentifi

The empirical investigations rely on data obtained from the Swiss FinTech start-up Sentifi. Sentifi was founded in 2012 with the goal to revolutionize the access to financial information and improve the information people use to make investment decisions (Sentifi (2019a)). The company has recognized that the financial information market is controlled by traditional information sources like newspapers, television or some financial information aggregator despite the fact that these sources make up only about ten per cent of the financial information available (Sentifi (2019a)). Sentifi uses artificial intelligence and machine learning to analyse, classify, and rank the other 90% of the available financial information (Sentifi (2019a)). Furthermore, Sentifi enables to streamline risk management by detecting political, societal, environmental, economic, and corporate risk events that impact global financial markets and assets (Sentifi (2019a)).

Sentifi offers a wide range of solutions for its costumers, starting with the basic version of the Sentifi Intelligence platform - which is provided free of charge - over additional modules for Sentifi Intelligence, to Sentifi API, which allows banks and investment firms to connect the alternative data with their existing systems. Since the basic version of Sentifi Intelligence already provides many exciting and helpful features, the author will briefly explain what kind of analyses Sentifi provides here. Figure 11 in the appendix shows the first view of the Sentifi Intelligence welcome page. At a glance, Sentifi Intelligence reports the indices, currencies, companies, people, commodities, and events that get the most attention over a certain period. Furthermore, it is possible to save companies, assets, and event types on watchlists.

By selecting a specific instrument, for example, an individual company, the user can find more detailed information regarding this company. Sentifi reports the absolute number of voices within the last 30 days talking about this company, as well as the relative change of attention during the last six hours and a chart that compares the number of voices per day to the end of day price. The company profile provides a summary of some key facts like a firm's industry, home country, and CEO. Every single voice can be viewed in its original form in the company's news feed, which is on the right side of the site. Furthermore, the main events concerning the company and potential risk events are visible below the chart. Finally, the top-ranked influencers speaking about the firm are presented at the bottom of the page in addition to a comparison with the main peers. An example of such a firm-specific page can be found in Figure 12 in the appendix.
The next subsection will provide an overview of how Sentifi extracts these insights from alternative financial information.

3.2 Collective Financial Intelligence - The Sentifi Engine

This subsection outlines the strategies, methodologies, and technologies used by Sentifi to extract the wisdom of the financial crowd from unstructured and structured data. The growth of social media has blurred the line between relevant news and irrelevant postings and articles considered as noise (Munz (2011)). Sentifi recognized this issue and avoids noise having a great impact on the analysis by not listening to everybody on social media (Reinhard (2019)). Therefore, Sentifi uses a combination of supervised and unsupervised machine learning to score the financial relevance of the content published by a source (Reinhard (2019)). If a source surpasses a certain score, it will be monitored and qualifies as an influencer. As the implementation of this procedure is very demanding and time-consuming, it is a unique selling point of Sentifi (Reinhard (2019)). At the moment, Sentifi has already processed 120 million sources, out of which only 14 million qualify as influencers and the engine is capable of processing two million new sources per day (Reinhard (2019)).

But the classification doesn't stop with the question of whether a source is an influencer or not. Sentifi uses a deep learning model to classify 17 different influencer categories such as executives, journalists, or activists. This model currently has an accuracy of 92% (Reinhard (2019)). The 17 different influencer categories are listed in the table I below.

Table I. Influencer Categories

The table presents the 17 influencer categories recognized by the Sentifi engine. (Source: Own representation based on Reinhard (2019))

Financial Market Professionals	**Other Stakeholders**
Brokers	Activists
Financial Advisors	General Public
Financial Analysts	Government Employees
Fund/Portfolio Managers	Journalists
Investor Relations	Legal & Compliance
Management	Media
Risk Professionals	Politicians
Retail Investors	
Traders	
Other Financial Professionals	

Sentifi takes into account that some influencers know more about specific companies than others. A CEO is almost certainly better informed about his company than an external stakeholder. Sentifi therefore not simply measures an influencer score in general, but by specific assets (Reinhard (2019)). The CEO mentioned before receives a high influencer score when talking about his company but a low score when talking about a completely different company. Sentifi calculates one specific influencer score for every asset discussed by the 14 million influencers, resulting in over 70 million influencer scores (Reinhard (2019)). Sentifi calculates these scores using a proprietary mathematical formula that takes a wide variety of data points into account

(Reinhard (2019)). Figure 1 provides an overview of this methodology.

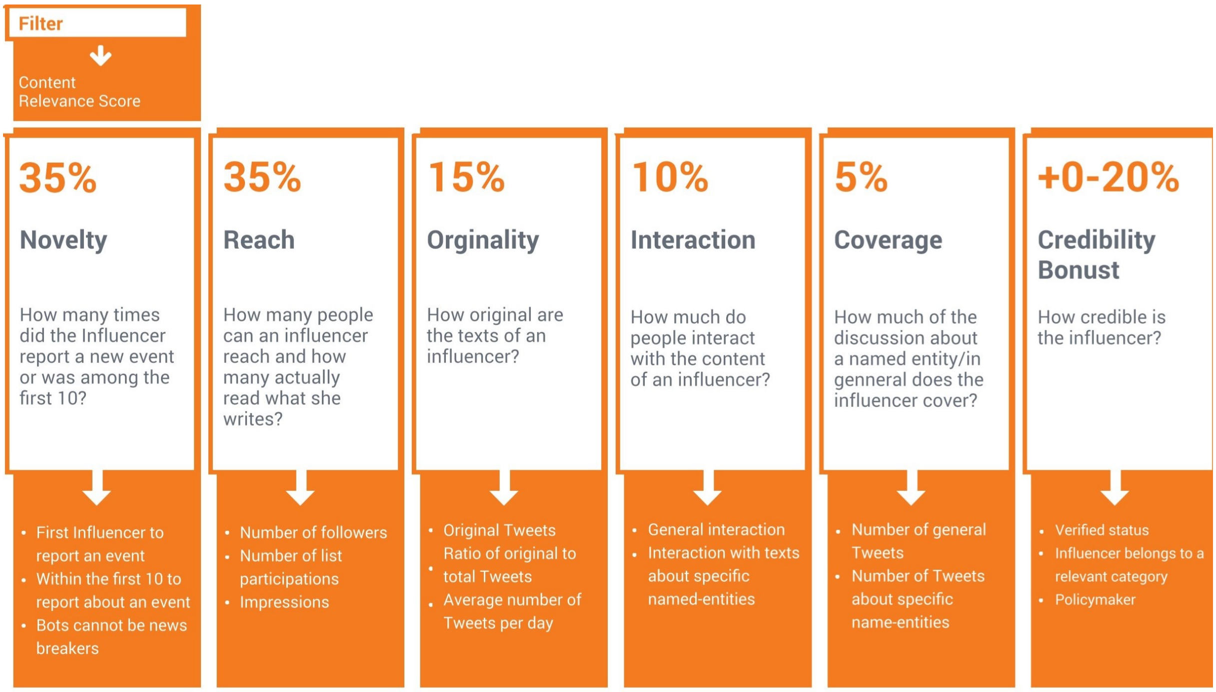

Figure 1. Influencer Score Methodology

Sentifi calculates a specific influencer score for every asset discussed by the different influencers. To calculate this scores a proprietary mathematical formula that takes a wide variety of data points into account is used. This figure provides an overview of this methodology. Source: Reinhard (2019)

Another important step to filter out the noise and focus on relevant news and signals is to score the relevance of the published content (Reinhard (2019)). The so-called "Content Relevance Score" is as well based on a combination of supervised and unsupervised machine learning and scores each news article, blog article and tweet published by the 14 million influencers (Reinhard (2019)).

An additional unique selling point of Sentifi is that they are following a global approach to recognise topics from the beginning (Reinhard (2019)). The keyword matching approach recognises 50'000 companies from all over the world, all currencies, the most popular cryptocurrencies and all major commodities with a precision of 99% and is capable of processing 1 billion news articles, blog articles and tweets per month (Reinhard (2019)).

Since it is nearly impossible for an investor to monitor 50'000 stocks, the questions arise, which companies should one take a closer look at? The simple answer to this question could be: the companies that get the most attention. However, this would result in always monitoring Apple, Amazon, Google, and other companies that get a lot of attention by nature. Therefore, Sentifi measures not only the absolute number of attention but also the percentage by which the attention for a topic deviates from the average attention (Reinhard (2019)). This metric is called "Attention vs. Moving Average" or "Attention-Buzz". To make it even easier to track the selected assets, Sentifi implemented a tool called "Event Recognition", which tells the user in two words, what event is being discussed (Reinhard (2019)). This helps the investors to quickly know why a particular company is receiving high attention without reading all the messages about this company. However, this tool can also be used vice versa if an investor is interested in companies that are discussed in relation to certain events, Sentifi is able to identify these companies (Reinhard (2019)). The tool currently recognises 300 different event types with 9'000 possible event names and has a precision of 87% (Reinhard (2019)).

Under consideration of all these metrics and tools, Sentifi calculates the "Sentiment-Score", which indicates the sentiment for each asset by assigning a score between -100 and +100 (Reinhard (2019)). To detect sentiment from text, Sentifi follows a two-step strategy, where the baseline model identifies the sentiment for the text as a whole. The higher-level model is target-specific and detects the sentiment for each company mentioned in the text individually (Reinhard (2019)). The sentiment score is updated every 15 minutes and calculated for different periods. This gives the investors insights about how positive or negative the sentiment for a specific company is and how it has developed over time (Reinhard (2019)).

Even though the Sentifi engine is already capable and precise, it is not yet fully developed, and there are several improvements in the developing process. First of all, the precision of the various models is to be further increased. Furthermore, Sentifi is currently developing its own deep event recognition capability, which enables the engine to detect and add new companies automatically and identifies connections between them. Additionally, it provides the capability to discover events in the future with yet unknown names (Reinhard (2019)). Text sentiment detection will also be further developed and expanded with supplementary models to identify target-specific sentiments for currencies, commodities, and other topics.

3.3 Dataset

3.3.1 Sample and Variables

The empirical evaluation is based on data from multiple sources. As already mentioned, the sentiment data is provided by Sentifi. These data from Sentifi contain the variables Attention-Volume, Attention-Buzz, daily Sentiment-Score, and Sentiment-Label. Table II gives a brief overview and provides a short description of these variables. Furthermore, Sentifi provides some firm-specific variables like sector, industry, legal name, and the ISIN number.

Table II. Sentifi variables

The table gives an overview and provides a short description of the variables of the Sentifi dataset.

Variable	Definition
Attention-Volume	The number of news articles, blog articles, and tweets by influencers that mention a topic over a defined time period.
Attention-Buzz	The percentage by which attention for a topic deviates from normal attention.
Sentiment-Score daily	Measures the sentiment for a topic on a score between -100 and +100, based on all news articles, blog articles, and tweets mentioning the topic per day.
Sentiment-Label	Labels the Sentiment-Score. Sentiment-Label is positive if aggregated Sentiment-Score is $\geq +33$, negative if aggregated Sentiment-Score is $\leq$ -33 and neutral if aggregated Sentiment-Score is between +33 and -33.

The sample period is from 01.12.2017 until 15.06.2019, which is the maximum period Sentifi can extract at the moment. The sample includes all stocks which were listed in the S&P 500 index, the Stoxx Europe 600 index and the Swiss Performance Index (SPI) as of 01.12.2017. This amounts to a total of 1'284 shares and a total of 738'468 daily Sentiment-Scores. In order to analyse the data, the overall sample is split into three subsamples, one for each index. The author therefore analyses data from three different regions: the USA, Europe, and Switzerland.

To supplement this data with company and market-specific information, Bloomberg's daily total return prices, daily market capitalization, and Bloomberg Ticker were extracted. The author has chosen the total return prices instead of the end of day prices since the total return prices are adjusted for dividends, stock splits, and stock issues. While the sentiment data is available for every weekday from Monday to Sunday including holidays, stock prices are only available on trading days. For better handling of the weekends, the variable weekday was included. This indicates which day of the week was on which date. Based on the total return prices, the author calculated the return for a stock i at a trading day t as follows:

$$Retrun_{i,t} = \frac{Price_{i,t}}{Price_{i,t-1}} - 1 \tag{1}$$

The market capitalization data is used to calculate the index return and portfolio weighting, as well as a proxy for firm size. Furthermore, since the available sentiment data is taken at the end of a calendar day, it is not possible to make the decision to buy a stock based on the sentiment data of the same day. Therefore, the additional variables "lag(Sentiment-Score)" and "lag(Attention-buzz)" are added. These variables represent the previous day's sentiment data. It is important to note here that a purchase decision on Monday should be based on the sentiment data of Sunday and not on those of the last trading day. Furthermore, during the process of forming strategies, additional variables are calculated and added based on the sentiment data.

Moreover, market factors and research returns have been directly downloaded from the publicly available website of Kenneth R. French, as well as the risk-free rate and the market risk premium (MktRF).[1] These factors will serve as additional control variables in this empirical study. The five Fama-French factors and the Momentum factor are explained in Table III. In this thesis, the US research returns data for the S&P 500 index, and the European research return data for the Stoxx Europe 600 index and the SPI index are used.

Table III. Market Factors

The table presents the five market factors used as control variables in this thesis and the definition of those factors.

Factor	**Definition**
Small Minus Big (SMB)	The average return on small stock portfolios minus the average return on big stocks portfolios.
High Minus Low (HML)	The average return on value portfolios minus the average return on growth portfolios.
Robust Minus Weak (RMW)	The average return on robust operating profitability portfolios minus the average return on weak operating profitability portfolios.
Conservative Minus Aggressive (CMA)	The average return on conservative investment portfolios minus the average return on aggressive investment portfolios.
Momentum (Mom)	The average return on high prior return portfolios minus the average return on low prior return portfolios

In summary, an observation in the used dataset contains the variables date, weekday, name, ISIN, Blomberg Ticker (Ticker), sector, industry, daily Sentiment-Score (sent score), Attention-Volume (attn vol), Attention-Buzz (attn buzz), lag(Sentiment-Score), lag(Attention-buzz), Sentiment-Label (label), total return (Return), market capitalization (MC), the five Fama-French factors (MktRF, SMB, HML, RMW , CMA), the risk free rate (RF) and the momentum factor (Mom). Both the ISIN number and the Bloomberg Ticker act as unique identifiers. Table XIX in the appendix provides an example excerpt of the dataset.

3.3.2 Descriptive Statistics

In the following subsection, the author provides some summary statistics for the main variables. Tables IV, VI and VII presents the mean, standard deviation, 25% and 75% percentiles, as well as the minimum and maximum values for the Sentiment Score, Attention-Buzz, Attention-Volume and Return for each of the three indices.

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html visited 19/06/2019

Table IV. Summary Statistics S&P 500

The table presents the mean, standard deviation, 25% and 75% percentiles, as well as the minimum and maximum values for the Sentiment-Score, Attention-Buzz, Attention-Volume and Return for the S&P 500 subsample.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
sent_score	274,739	14.109	24.613	−99.146	0.000	29.630	98.797
attn_buzz	236,442	10.117	65.196	0.000	0.636	3.727	6,824.727
attn_vol	282,686	110.003	700.785	0.000	7.000	41.000	75,073.000
Return	196,231	0.0003	0.017	−0.418	−0.007	0.009	0.454

Since the subsample for the S&P 500 contains the most complete data, the author will go into this sample in more detail. First, we want to look at the distribution of the Sentiment-Score to see if the overall market sentiment is more positive or negative. The average value of 14,109 is slightly positive, which is an indicator that the market sentiment is rather positive. From the total of 274'739 reported Sentiment-Scores, 59'150 (21.53%) are above the threshold of 33 and hence labelled positive, while only 8298 (3.02%) are below -33 and labelled negative. If we take a look at the density function in figure 2, we see that the Sentiment-Score is more or less normally distributed around the mean, but with an outlier around zero.

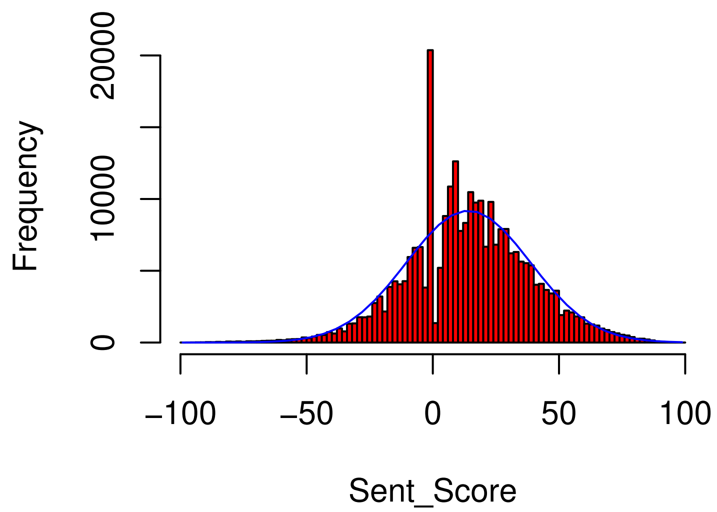

Figure 2. **Histogramm with Normal Curve S&P 500**

The figure draws the density function of the Sentiment-Score with plotted normal curve. The underlining data is the S&P 500 subset.

This can be explained by the fact that most companies receive little or no attention on twitter and blogs during normal business development, which results in a Sentiment-Score of zero.

Furthermore, it is interesting to take a closer look at the maximum Attention-Volume and the maximum Attention-Buzz and see what caused these very high numbers compared to the means of these metrics. These high figures belong to the company Boeing and were triggered by the crash of a Boeing 737 Max 8 on 10 March 2019 and the subsequent discussion about the grounding of this air-plane type. Table V provides an overview of the sentiment data from 10 March to 15 March 2019.

Table V. Excerpt of Boeing from 10.03.2019 - 15.03.2019

This table show the high Attention-Volume and Attention-Buzz of Boeing triggered by the crash of a Boeing 737 Max 8 on 10 March 2019 and the subsequent discussion about the grounding of this air-plane type until 15 March 2019.

isin	Name	date	weekday	attn_buzz	attn_vol	sent_score	Return
US0970231058	Boeing Co/The	2019-03-10	Sunday	629	6920	-67.42	NA
US0970231058	Boeing Co/The	2019-03-11	Monday	1679.09	18471	-39.15	-0.05
US0970231058	Boeing Co/The	2019-03-12	Tuesday	3857.18	42430	-38.20	-0.06
US0970231058	Boeing Co/The	2019-03-13	Wednesday	6824.72	75073	-13.54	0.005
US0970231058	Boeing Co/The	2019-03-14	Thursday	2152	23673	-34.73	-0.01
US0970231058	Boeing Co/The	2019-03-15	Friday	841.55	9258	-33.84	0.02

One notices that the high attention after the crash was mainly negative, resulting in a high negative sentiment score. Furthermore, one can see that the combination of deep sentiment scores and high attention volume or high attention buzz leads to negative returns. This connection will be examined in more detail (see table VIII) and kept in mind for the development of the strategy.

Table VI. Summary Statistics Stoxx Europe 600

The table presents the mean, standard deviation, 25% and 75% percentiles as well as the minimum and maximum values for the Sentiment-Score, Attention-Buzz, Attention-Volume and Return for the Stoxx Europe 600 subsample.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
sent_score	230,336	12.541	21.189	−98.118	0.000	23.077	98.230
attn_buzz	245,391	2.993	26.231	0.000	0.000	1.273	5,495.545
attn_vol	334,390	29.735	255.492	0.000	0.000	13.000	60,452.000
Return	227,505	0.0002	0.017	−0.475	−0.008	0.008	0.896

In order to measure whether the general market sentiment in Europe differs from that in the USA, we look at the mean and the number of positive or negative Sentiment-Scores in the Stoxx Europe 600 data set. As before, the mean is slightly positive at 12.54, which indicates a rather positive market sentiment. From the total of 230'336 reported Sentiment-Scores, 35'410 (15.37%) are above the threshold of 33 and hence labelled positive, while only 4474 (1.94%) are below -33 and labelled negative. The Sentiment-Scores are similarly distributed as with the S&P

500, even if there are significantly more Sentiment-Scores that are neutrally labelled. The reason for this could be that Twitter is much more widespread and used in the United States, resulting in much deeper Attention-Volumes and more companies receiving no or very little attention in Europe, leading to a neutrally labelled Sentiment-Score. This is also clearly visible in the mean Attention-Volume, which is significantly lower in the Stoxx Europe 600 subset than in the S&P 500 subset.

Table VII. Summary Statistics SPI

The table presents the mean, standard deviation, 25% and 75% percentiles as well as the minimum and maximum values for the Sentiment Score, Attention-Buzz, Attention-Volume and Return for the SPI subsample.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
sent_score	39,845	10.826	18.084	−89.950	0.000	17.391	94.788
attn_buzz	99,381	0.785	20.653	0.000	0.000	0.000	5,495.545
attn_vol	120,268	8.557	207.833	0	0	1	60,452
Return	79,799	−0.0001	0.023	−0.762	−0.007	0.007	1.242

The same trend can also be seen in the Swiss data, as the average sentiment score is a little lower and only 11.37% of it can be labelled positive and 0.95% negative. The share of neutral Sentiment-Scores is, therefore, rising again.

To get an initial overview of whether and how sentiment metrics and return interact, table VIII reports the pairwise correlations between selected variables included in the analysis. For the S&P 500 and the Stoxx Europe 600 index we observed positive correlations between Sentiment-Score, Sentiment-Score Lag, and Return and negative correlation between Sentiment-Score, Attention-Buzz and Attention-Buzz Lag. Furthermore, Attention-Buzz and Attention-Buzz Lag are weakly negatively correlated to the return. This underlines the relationship we have already supposed analysing the Boeing example. Important to notice is, that the two main explanatory variables Sentiment-Score and Attention-Buzz or rather Sentiment-Score Lag and Attention-Buzz Lag are only weakly correlated. Hence, we don't have to worry about multicollinearity.

Since the empirical analysis in this thesis is divided into two parts, different dependent and independent variables are needed. In the first part, different portfolios were created using different strategies. These strategies are based on the sentiment metrics Sentiment-Score and Attention-Buzz. These variables therefore serve as independent variables when calculating portfolio returns. In a second step, these portfolio returns will be explained using market factors. In this part, the portfolio returns, more precisely the portfolio returns minus the risk-free interest rate, serve as dependent variables and the market factors explained in table III as independent variables. Section 4 subsequently goes into detail on the empirical methods and techniques used.

Table VIII. Correlation Matrix

The table reports the pairwise correlations between selected variables. The sentiment data are from Sentifi and the stock price data from Bloomberg. Panel A shows the correlations for the S&P 500 subset. Panel B shows the correlations for the Stoxx Europe 600 subset. Panel C shows the correlations for the SPI subset.

	sent_score	sent_score_lag	attn_buzz	attn_buzz_lag	Return
A: S&P 500					
sent_score	1	0.363	-0.032	-0.030	0.098
sent_score_lag	0.363	1	-0.023	-0.025	0.018
attn_buzz	-0.032	-0.023	1	0.782	-0.009
attn_buzz_lag	-0.030	-0.025	0.782	1	-0.003
Return	0.098	0.018	-0.009	-0.003	1
B: Stoxx Europe 600					
sent_score	1	0.433	-0.038	-0.036	0.097
sent_score_lag	0.433	1	-0.023	-0.030	0.017
attn_buzz	-0.038	-0.023	1	0.483	-0.002
attn_buzz_lag	-0.036	-0.030	0.483	1	-0.003
Return	0.097	0.017	-0.002	-0.003	1
C: SPI					
sent_score	1	0.392	0.008	0.0004	0.059
sent_score_lag	0.392	1	-0.005	0.010	0.027
attn_buzz	0.008	-0.005	1	0.500	0.002
attn_buzz_lag	0.0004	0.010	0.500	1	0.002
Return	0.059	0.027	0.002	0.002	1

4 Method

The empirical part of this thesis consists of an introduction to the theory of strategy backtesting with a particular focus on risks and dangers, as well as an introduction to the theory of abnormal returns. Moreover, trading strategies will be developed and tested.

4.1 Backtesting Theory

According to Bailey, Borwein, de Prado, and Zhu (2014) a backtest is a historical simulation of how a particular algorithmic investment strategy would have performed in the past. Among other things, a backtest computes the profit and losses that a strategy would have generated, had that algorithm been run over a specific period (Bailey, Borwein, de Prado, and Zhu (2014)). It is important to notice, that although backtesting is a necessary and powerful research tool, it can be very easily manipulated, such that after a sufficient number of trials, it is guaranteed that a researcher will find a profitable strategy (Bailey and de Prado (2014)). In this regard, over-fitting and curve-fitting are often referred to. These problems arise when more than one strategy configuration is tested because the new strategies are always influenced by the knowledge about the historical data (Low, Maier Paape, and Platen (2017)). Such strategies, that have been designed to profit from a random pattern present in the past, are unlikely to perform well in the future since it is unlikely, that the future movements in stock price equal the ones in the past. Furthermore, backtest over-fitting tends to identify strategies that profit from the most extreme random patterns in the sample, which are also the least likely patterns to repeat in the future (Bailey and de Prado (2014)). Unfortunately, many academic studies that identify profitable investment strategies rely on such misleading over-fitted backtests (Bailey, Borwein, de Prado, and Zhu (2014)).
Therefore, it is important to include several pieces of information that make it possible to assess the relevance of a backtest (Bailey and de Prado (2014)). In particular, it is inevitable to report the number of trials attempted to find the outperforming strategy as well as metrics to report the risk-adjusted return such as the Sharpe Ratio or the Information ratio (Bailey and de Prado (2014)).

Since over-fitting is a concept that originates from machine learning, the proposed solution to mitigate the problem also comes from this area (Bailey, Borwein, de Prado, and Zhu (2014)). Cross-validation and holdout tests are usually considered to mitigate over-fitting, but only the latter is also used in finance to test investment strategies. With the holdout method, also called out of sample (OOS) test, the data set is usually divided into two disjoint partial data sets, with only the first part used to estimate the model parameters or, in this case, to determine the investment strategy (Kuhlmann (2009)). This first subset is usually called training dataset. The other part of the data set is called holdout - or test set. This part is explicitly not used for the strategy determination but only for checking the strategy (Kuhlmann (2009)). The investment strategy is therefore applied to data that previously had no influence on the design of the strategy.
If several different strategies are to be tested, it is also possible to divide the total data set into

three sub-sets, whereby the validation data set is added (Kuhlmann (2009)). The validation data set is only used for the selection of one of the different strategies. According to Snee (1977), time-series data can easily be split by date, noting that the test data set consists of earlier data and the holdout sample uses more recent data. Furthermore, it is important that the individual partial data sets are large enough so that sufficient degrees of freedom is guaranteed in the empirical evaluation (Kuhlmann (2009)).

Unfortunately, the holdout method has several limitations (Harvey, Liu, and Zhu (2015)). First of all, if the dataset is split into two subsets, a researcher has exactly one chance to test its strategy on the holdout set and if the strategy fails and the researcher wants to review and retry the strategy, it becomes more of a trial and error approach than real out of sample testing (Harvey, Liu, and Zhu (2015)). Even if there is an additional valuation set, it is possible that the chosen strategy fails on the test set and we are in the same situation as before. Moreover, the author assumes, that almost all researchers and practitioners who test investment strategies have a certain knowledge about the stock market and the economy. Therefore, it is theoretically impossible to construct a true out of sample test because the tester already knows what happened in the economy and on the stock market (at least to a certain extent) (Harvey, Liu, and Zhu (2015)).

Furthermore, even when the backtest is executed seriously, and the estimated performance is satisfying, one can never be sure that the true performance is above a certain threshold because there could arise two different types of errors due to data splitting (Bailey and de Prado (2014)). The type I error, also called a false positive, occurs when a strategy is chosen that should have been discarded (Bailey and de Prado (2014)). Type II, also called a false negative, occurs when a strategy that should have been chosen is discarded (Bailey and de Prado (2014)). While these two errors also occur in in-sample testing, out of sample testing increases the chance of a Type II error (Harvey, Liu, and Zhu (2015)). Practitioners are more concerned about the type I error, since they would rather exclude a true strategy than risking to apply a false one (Bailey and de Prado (2014)). Therefore, it is important to not test too many strategies, as the more strategies tested, the greater the likelihood of a Type I error (Bailey and de Prado (2014)).

Another problem one has to be aware of is the so-called selection bias. It's about the fact that researchers and journals tend to publish only the positive outcome, and the negative ones are not reported at all (Bailey and de Prado (2014)). By doing so, critical information is hidden, and the type I error probability is much larger than anticipated (Bailey and de Prado (2014)). This thesis is intended to address this problem by reporting all trials and relevant metrics to asses the relevance of the backtest.

As already mentioned before, one of these metrics is the Sharpe Ratio first introduced by Sharpe (1966). It is the most widely used performance statistic and evaluates an investment in terms of returns on risks as opposed to return on capital (Sharpe (1994)). Given the mean return of a portfolio with zero initial investment ($\hat{\mu}$) and the standard deviation of this return ($\hat{\sigma}$), the

Sharpe Ratio is defined as:

$$\widehat{SR} = \frac{\hat{\mu}}{\hat{\sigma}}. \tag{2}$$

If we compare equation 2 with a t-statistic constructed to test the null hypothesis that the average return is zero, which is defined as:

$$t - ratio = \frac{\hat{\mu}}{\hat{\sigma}/\sqrt{T}} \tag{3}$$

with T is the number of observations, it is visible that the Sharpe Ratio is simply the $t - ratio$ divided by $\sqrt{T}$ (Harvey, Liu, and Zhu (2015)). Hence, a higher Sharpe Ratio implies a higher significance level for the strategy, assuming that T is fixed (Harvey, Liu, and Zhu (2015)). Even though the Sharpe Ratio is a useful concept, it can be misleading, as it can also be affected by the selection bias and over-fitting arising with multiple testing (Harvey, Liu, and Zhu (2015)). But since multiple testing is a useful tool, it should not be abused but rather carefully planned in advance to avoid running an unnecessarily large number of trials (Bailey and de Prado (2014)). Bruss (1984) provides with the theory of optimal stopping an elegant answer to the question, what the maximum number of trials should be and calls the result the e^{-1}-law. It testifies that one should sample a random fraction e^{-1} of the theoretically justifiable strategies and afterwards test new strategies one by one until one is found that beats all the previous (Bailey and de Prado (2014)). This last strategy should be selected, and no more trials made.

Since the number of theoretically justifiable strategies that could be made with the unique data from Sentifi is quite large and the observation period rather small, this approach would lead to a far too large number of trials resulting in over-fitting. As a consequence, the author abstains from this and only carries out a comparatively small number of five trials to prevent over-fitting. Furthermore, it is not possible to divide the data set by date and make an out of sample test due to the short period. As an alternative, the data record is divided among the three available indices. In order to minimize the probability of over-fitting, the strategies are only developed on the S&P 500 subset and afterwards applied to the other two subsets. In this approach - which could be called a "cross-section out of sample test" - the S&P 500 subset serves as the training set and the other two subsets serve as the test sets.

4.2 Abnormal Returns Theory

Once one has backtested an investment strategy, one knows whether it has performed better or worse than the benchmark in the past. But you still don't know what the driver of this additional return was. In this case, sentiment data could simply reflect expected returns and thus not provide any additional insights. In this subsection, the author explains the relationship between expected and abnormal returns and how to test whether, the sentiment data provides abnormal returns or simply reflect more loadings on economic risk factors.

The concept of abnormal returns is borrowed from the event study technique and makes it possible to isolate the effect of the stock specific reaction to the sentiment data (Hafez (2009)).

According to Bodie, Kane, and Alan (2014) an event study describes a widely accepted technique of empirical research that enables an observer to assess the economic impact of a wide range of events on a firm's stock price.
There exist several techniques on how to measure and adjust the normal or expected return. The first technique to name is the capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965):

$$E[R_i] = RF + \beta_i * (Mkt - RF) + \epsilon_t \tag{4}$$

Whereby $E[R_i]$ stands for the expected return of a stock or a portfolio of stocks, RF for the risk free rate, β_i for the equity beta and Mkt for the marked return.
Additionally, the author considers other asset pricing models, such as the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, the Carhart (1997) four-factor model and finally the Fama and French (2015) five-factor model extended by the momentum factor from Carhart (1997).

The Fama and French three-factor model expands the CAPM and captures the relation between the average return and market capitalization and the relation between average return and the Book to Market ratio:

$$E[R_i] = RF + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t \tag{5}$$

Whereby SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks and HML_t is the difference between the returns on diversified portfolios of high and low book to market stocks (Fama and French (1993)). The abnormal or excess return is given by the difference between the realized portfolio or stock return R_i and the expected return $E[R_i]$. To run tests on these asset pricing models, we need to rearrange the respective equations as shown here with the example of equation 5:

$$\begin{aligned} E[R_i] &= RF + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t \\ \alpha_i &= R_i - E[R_i] \\ R_i - RF &= \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t \end{aligned} \tag{6}$$

whereby the intercept α_i stands for the generated abnormal return. Because Novy-Marx (2013) provided evidence, that the three-factors model misses much of the variation in average returns related to profitability and investment, therefore it is perceived as an incomplete model for expected returns. Therefore, Fama and French (2015) added profitability and investment factors and came up with the five-factors model:

$$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t \tag{7}$$

The new factors RMW_t and CMA_t stand for the difference between the returns on diversified portfolios of stocks with robust and weak profitability and the difference between the returns on diversified portfolios of the stocks of low and high investment firms (Fama and French (2015)). Other then Fama and French, Carhart (1997) did not add profitability and investment factors to the three-factors model, but an additional factor to capture the one year momentum anomaly found by Jegadeesh and Titman (1993):

$$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + p_i * MOM_t + \epsilon_t \tag{8}$$

Where MOM_t stands for the difference between the returns on diversified portfolios of stocks with high and low momentum (Carhart (1997)). The last model considered is a combination of the Fama and French (2015) five-factor model and the momentum factor by Carhart (1997):

$$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t \tag{9}$$

To test whether a strategy generates excess return, the author runs time series regressions on the mentioned models. If the exposure to the respective factors capture all variation in expected returns, the intercept α_i would be zero. If there is excess return, the intercept is positive. Since the author considers the last model (equation 9) to be the most complete, equation 9 serves as the main model, while the other models are used to test the robustness.

4.3 Portfolio Strategies

The design of an investment strategy usually begins with a belief, that certain data may help forecast future stock prices. This thesis is based on the belief that the Sentifi data - especially the Sentiment-Score and the Attention-Buzz or a combination of both - predict stock prices or at least the direction in which they will move.

The main objective in this sub-section is to develop realistic and tradable strategies that anyone with access to the Sentifi data can apply. Therefore, the strategy should be simple and understandable and should not contain complex mathematical optimization problems. In order to avoid overfitting, the strategies are developed using only the S&P 500 subset and then tested against the other subsets. This has already been explained in detail in subsection 4.1.
In order to evaluate, whether the strategies were successful, the first step is to compare them with the benchmark. The benchmark is based on the respective market-weighted index. In a second step, it will be investigated whether any excess returns have been generated due to the sentiment data, or if they simply reflect more loadings on economic risk factors. This procedure is explained in detail in subsection 4.2. While the comparison of strategies is shown in this section, the analysis of abnormal returns is shown in section 5.

To get an idea if it is even possible to develop a strategy that beats the benchmark, the author will first apply a simple long/short strategy that is rebalanced daily. The author accesses the Sentiment-Label, which shows a positive sign for Sentiment-Scores above or equal 33 and a negative sign for scores below or equal -33. In the stocks that had a positive labelled score at the end of the previous day, a long position should be taken and in those that had a negative

labelled score a short position. In addition, the Attention-Buzz should also be considered, as the author assumes that the Sentiment-Score only influences the share price if there is certain untypical attention. Therefore, only positions in stocks with an above-average Attention-Buzz are considered. In this and all subsequent strategies, the author assumes that markets are sufficiently liquid. This means that all orders are filled at the requested price.
The result of running this strategy over the period from 05. March 2018 until 14. June 2019 is shown in figure 3.

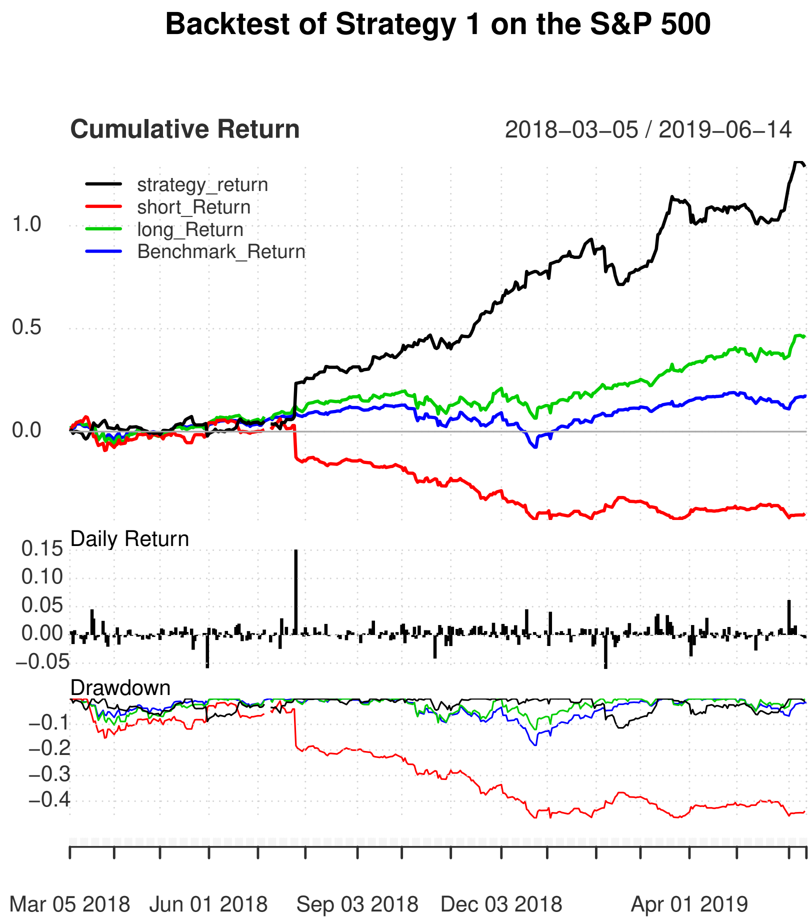

Figure 3. **Backtest of Strategy 1 on the S&P 500**

The figure presents the result of backtesting strategy 1 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolios are rebalanced every day. The first part of the figure shows the cumulative return of the benchmark (blue), the long portfolio (green) the short portfolio (red), and the total portfolio (black). The second section shows the daily return of the total portfolio and the third section the drawdowns of each portfolio and the benchmark.

The chart shows that a portfolio built with the long/short strategy performs better than the benchmark. Both the long strategy and the short strategy perform better than the benchmark. To get the total portfolio return, we have to subtract the returns of the short portfolio from the returns of the long portfolio. Table IX provides the annualized return, annualized standard deviation, and the annualized Sharpe Ratio for the benchmark and the long/short portfolio.

Table IX. Annualised performance statistics strategy 1

The table presents the annualised performance statistics from the backtest of strategy 1 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolios are rebalanced every day. The annualised return, standard deviation, and Sharpe Ratio are shown for the benchmark, the short portfolio, the long portfolio, and the overall portfolio.

	Benchmark Return	short Return	long Return	strategy Return
Annualized Return	0.1264	-0.3187	0.3379	0.8700
Annualized Std Dev	0.1540	0.2740	0.1885	0.2369
Annualized Sharpe Ratio (RF = 0%)	0.8206	-1.1633	1.7926	3.6732

The annualized buy and hold return of the S&P 500 Portfolio for the considered period is 12.64% while the portfolio built with the long/short strategy based on the Sentifi data get an annualized return 87.00%. Furthermore, the annualized Sharpe Ratio of 3.67 at a risk-free rate of 0% implies that the long/short portfolio has better risk-adjusted returns than the benchmark with a Sharpe Ratio of 0.8205.

While these figures clearly show that it should be possible to develop a strategy that outperforms the benchmark, this long/short strategy has some serious drawbacks which are to be eliminated in the other strategies. The first issue to mention here is the large number of trades. During the period under review, 4372 trades were executed with this strategy. Note here, that a trade consists of two actions - one to open the position and one to close it. Since the returns stated are without transaction costs, the transaction costs incurred by 4372 trades would significantly reduce the return. In addition, 2331 of these trades show a positive return and 2027 a negative return. The trade signal therefore only leads to a positive return in just over 53% of the cases. Hence, a trade signal should be found, which results in a larger percentage of trades with positive returns. This is to be achieved by increasing the limit for the required Sentiment-Score or by observing the development of the sentiment over a period of time instead of only deciding based on the previous day's Sentiment-Score.

Furthermore, one must be aware that this long/short strategy with a standard deviation of 23.69% is significantly riskier than the benchmark and in addition, the strategy shows a maximum loss of 6.01% in one day, which is substantial. Since the average holding period of the shares is just 2.57 days, the author extends the rebalancing period in the other strategies.

The author tries to solve the problems of the long/short strategy in the first step with a so-called "moving average strategy". Two moving averages of different lengths are compared. The signals

are given by the direction of the crossing of the two moving averages. These signals are to buy as soon as the shorter period moving average crosses the longer period moving average from bellow and to sell when the shorter period moving average crosses the longer period moving average from above (Ellis and Parbery (2005)). In this case, two moving averages of the Sentiment-Score are calculated, one over 10 trading days and one over 40 trading days. The aim of this is to somewhat smooth out the high volatility of the Sentiment-Score, thereby increasing the holding period of the shares and reducing the number of trades.
Figure 6 illustrates how this strategy works using the company Boeing as an example. The red line marks the longer moving average of the Sentiment-Score and the blue line the shorter one. As soon as the blue line crosses the red line from below, the Boeing share will be bought, and as soon as the blue line crosses the red line from above, the share will be sold again.

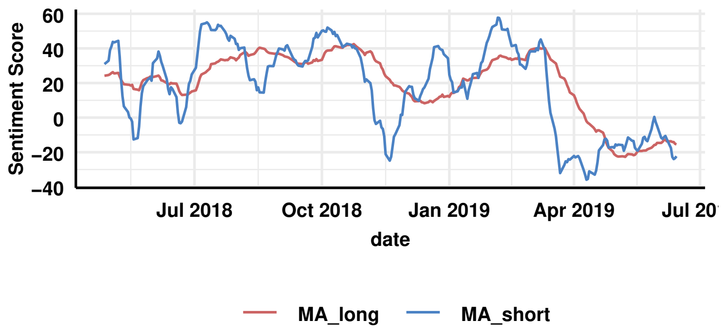

Figure 4. Moving Averages of Boeings Sentiment Score

The figure illustrates the principle of the moving average strategy using the example of the Boeing company. The red line marks the moving average over 40 trading days of the sentiment score and the blue line the moving average over ten trading days. As soon as the blue line crosses the red line from below, the Boeing share will be bought, and as soon as the blue line crosses the red line from above, the share will be sold again.

The result of running the moving average strategy over the period from 05. March 2018 until 14. June 2019 is shown in figure 5. As with the long/short strategy, the performance indicators look very good at first glance. The chart in figure 5 shows that the portfolio built with the moving average strategy outperforms the benchmark over the observed period. Furthermore, table X provides the annualized return, standard deviation, and Sharpe Ratio at a risk-free of 0%.
At 19.94%, the return on the portfolio built with the moving average strategy is significantly lower than that of the long/short strategy. On the other hand, the strategy has a standard deviation of 14.88% and is therefore less risky than the long/short strategy. Compared to the benchmark, both the return and the Sharpe Ratio are better.

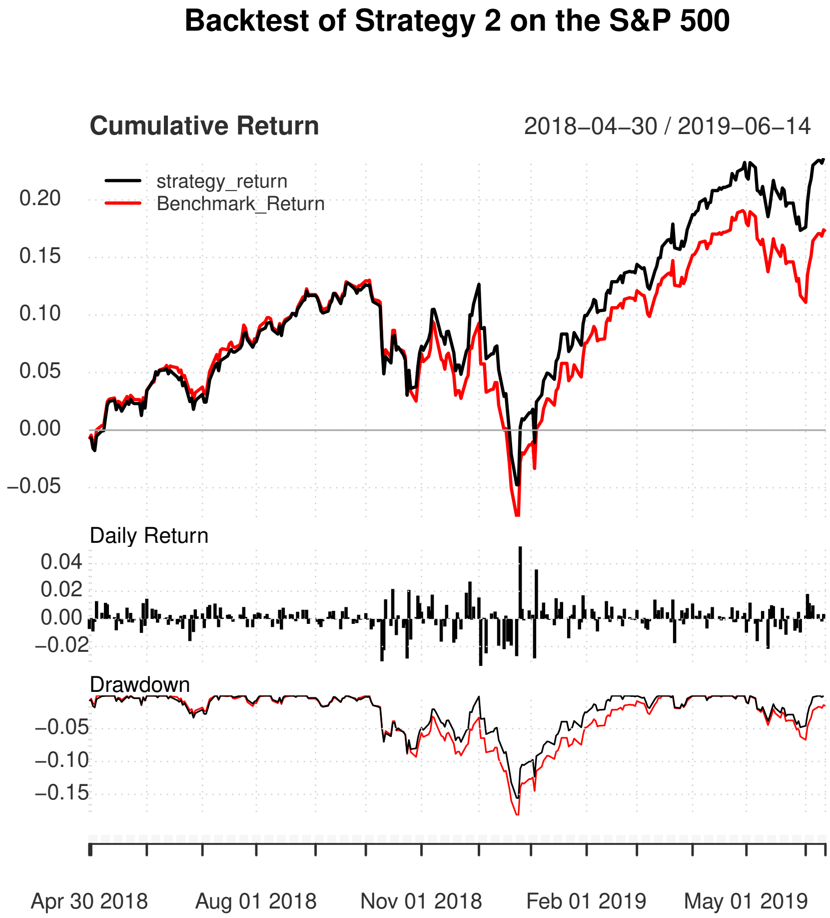

Figure 5. Backtest of Strategy 2 on the S&P 500

The figure presents the result of backtesting strategy 2 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 2 is a moving average strategy where stocks will be bought as soon as the 10 trading day moving average crosses the 40 trading day moving average from below, and sold as soon as the 10 trading day moving average crosses the 40 trading day moving average from above. The portfolio is rebalanced every day. The first part of the figure shows the cumulative return of the benchmark (red) and the built portfolio (black). The second section shows the daily return of the portfolio and the third section the drawdowns of the portfolio and the benchmark.

Table X. Annualised performance statistics strategy 2

The table presents the annualised performance statistics from the backtest of strategy 2 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 2 is a moving average strategy where stocks will be bought as soon as the 10 trading day moving average crosses the 40 trading day moving average from below, and sold as soon as the 10 trading day moving average crosses the 40 trading day moving average from above. The portfolio is rebalanced every day. The annualised return, standard deviation and Sharpe Ratio is shown for the benchmark and the portfolio built with strategy 2.

	Benchmark Return	Strategy Return
Annualized Return	0.1264	0.1994
Annualized Std Dev	0.1540	0.1488
Annualized Sharpe Ratio (RF = 0%)	0.8206	1.3406

Despite the fact that the second strategy looks promising, it remains to be seen whether the disadvantages of the first strategy have been mitigated. Unfortunately, the moving average strategy did not have the desired effect in terms of the number of trades, and during the period under review, 7558 trades were executed. While 55.00% of those trades had a positive return, 44.80% had a negative one. This is slightly better than with the strategy before but still a far to high share of negative trades. What has improved significantly, however, is the average holding period of the shares, which is now 12.93 days.
Since both previous strategies are not completely satisfactory in terms of the number of trades and the proportion of negative trades, further strategies are being developed to reduce these disadvantages. Both the buy signal, which is composed of the Sentiment-Score and the Attention-Buzz, and the signal based on average Sentiment-Scores have delivered good performance results for the first two strategies. Therefore, the next strategy should also be based on these indicators. In order to reduce the number of trades and create a buy signal that leads more reliably to positive trades, the portfolio should only be rebalanced on a weekly basis and not be based solely on the Sentiment-Score of one day. In addition, only a long strategy is used to keep the risk somewhat lower.
The strategy is mainly based on the weekly average Sentiment-Score. A stock should be bought if the average Sentiment-Score of the previous week was at least 33. In addition, only those stocks are to be bought, which received above-average attention in the previous week. The shares that meet these two conditions will be bought on Monday and hold for one week. On the following Monday, it will be evaluated whether the share remains in the portfolio or is sold again. The result of running this third strategy over the same period as before is shown in figure 6. Again, the cumulative performance of the portfolio built with strategy 3 over the period under review outperforms that of the benchmark. Furthermore, the annualised return and Sharpe Ratio - shown in table XI - are also better than those of the benchmark. This third strategy had the desired effect on the number of trades. These have now dropped sharply, and 328 trades have been executed. The development of the holding period is also pleasing; the shares are now held for an average of 14.45 days. Unfortunately, the share of negative trades is even higher than before at 48.48%.

Table XI. Annualised performance statistics strategy 3

The table presents the annualised performance statistics from the backtest of strategy 3 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 3 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous week is at least 33. In addition, only stocks with an above-average previous week average Attention-Buzz are considered. The portfolio is rebalanced every Monday. The annualised return, standard deviation, and Sharpe Ratio are shown for the benchmark and the portfolio built with strategy 3.

	Benchmark Return	Strategy Return
Annualized Return	0.1264	0.1740
Annualized Std Dev	0.1540	0.1990
Annualized Sharpe Ratio (RF = 0%)	0.8206	0.8744

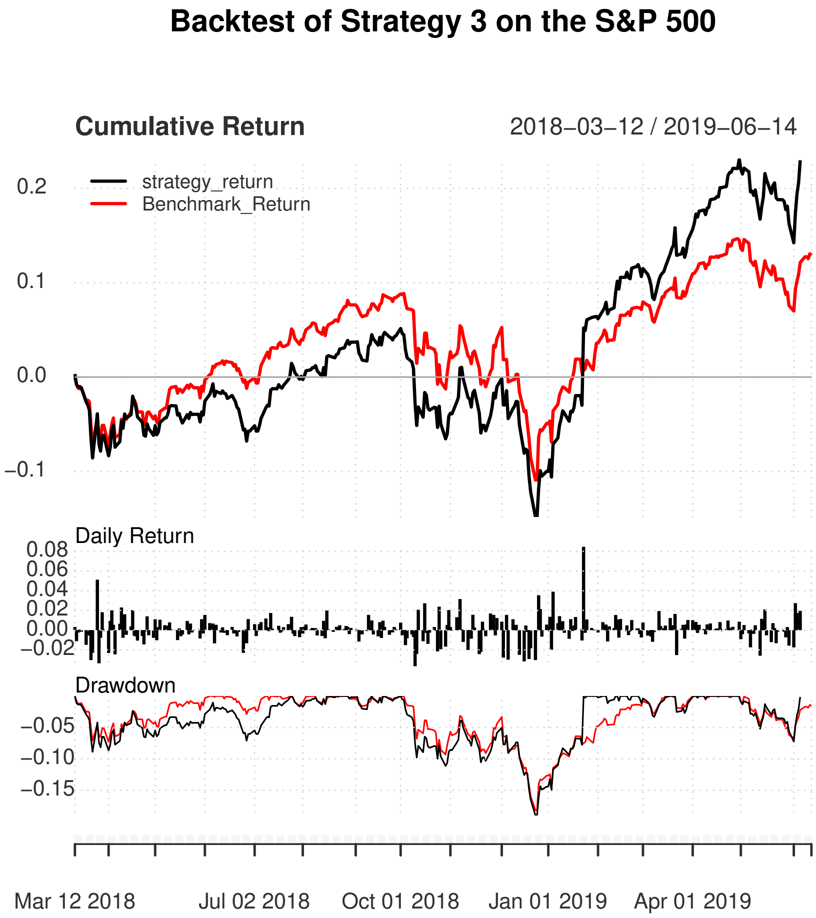

Figure 6. **Backtest of strategy 3 on the S&P 500**

The figure presents the result of backtesting strategy 3 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 3 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous week is at least 33. In addition, only stocks with an above-average previous week average Attention-Buzz are considered. The portfolio is rebalanced every Monday. The first part of the figure shows the cumulative return of the benchmark (red) and the built portfolio (black). The second section shows the daily return of the portfolio and the third section the drawdowns of the portfolio and the benchmark.

As pre-defined in subsection 4.1, a maximum of five strategies are developed and tested to prevent over-fitting. This means that there are still two trials left to solve the problem with the high percentage of negative trades. The next attempt is a modified version of the previous strategy. The rebalancing period is extended to one month, and the buy signal is given by a monthly average Sentiment-Score of at least 33 and above-average attention (measured via average the Attention-Buzz) in the previous month.
The direct consequence of this is that the holding period of the shares in the portfolio rises to 79.76 days, and only 59 trades are executed. As a result, any transaction costs are no longer of such great impact. Figure 7 reveals the results obtained when running strategy 4 during the available period and Table XII shows the corresponding data on the annualized return, standard

deviation and Sharpe Ratio.

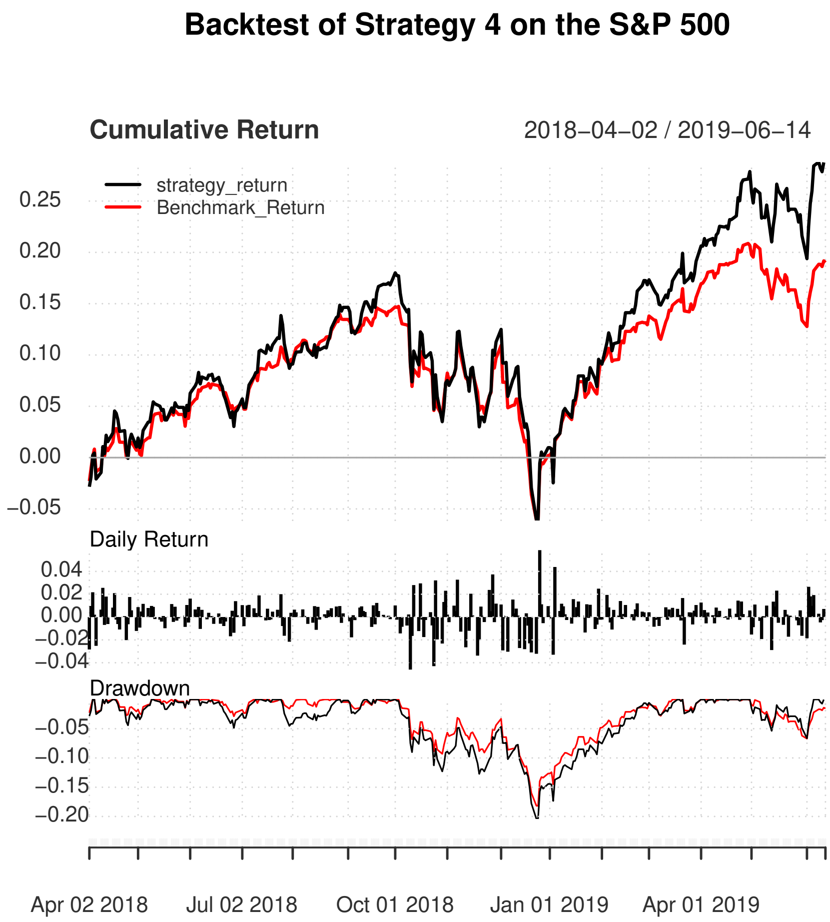

Figure 7. Backtest of strategy 4 on the S&P 500

The figure presents the result of backtesting strategy 4 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. The first part of the figure shows the cumulative return of the benchmark (red) and the built portfolio (black). The second section shows the daily returns of the portfolio and the third section the drawdowns of the portfolio and the benchmark.

Again, the strategy beats the benchmark. The modification leads to a higher annualized return and a higher Sharpe Ratio compared to strategy 3. In addition, the standard deviation of 20.34% is only slightly larger than that of the third strategy of 19.90%. The modification thus leads to a significantly better risk/return ratio. The percentage of negative shares however is still much too high and amounts to 47.46%.

Table XII. Annualised performance statistics strategy 4

The table presents the annualised performance statistics from the backtest of strategy 4 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. The annualised return, standard deviation, and Sharpe Ratio is shown for the benchmark and the portfolio built with strategy 4.

	Benchmark Return	Strategy Return
Annualized Return	0.1264	0.2250
Annualized Std Dev	0.1540	0.2023
Annualized Sharpe Ratio (RF = 0%)	0.8206	1.1119

The last approach to solve the problem of the high share of trades with negative performance is to focus only on the Sentiment-Score as a buy signal. The idea behind this is that only the companies that the influencers are the most positive about are bought. This should give a clear signal that leads to a larger share of positive trades. The strategy is to buy every week the ten companies with the highest average Sentiment-Score during the previous week. If this strategy is run over the observed period from 5 March 2018 to 6 June 2019, a total of 421 trades are executed. The new strategy has led to a slight improvement in the percentage of negative trades. Out of the 421 trades executed, 180 show negative performance, corresponding to 42.76% of the total. This means that strategy 5 performs best in terms of this criterion.

However, if one looks at the performance of the portfolio built with strategy 5, it becomes obvious that in this respect, the results are not convincing. Figure 8 shows the result obtained when backtesting the strategy during the available period and Table XIII shows the corresponding data on the annualized return, standard deviation and Sharpe Ratio. Although the strategy outperforms the benchmark in terms of cumulative and annualized return, it has a lower Sharpe Ratio than the benchmark and thus, the lowest Sharpe Ratio of all the strategies tested. This means that one is not compensated for the additional risk taken - i.e. for a higher standard deviation - with a sufficiently higher return.

This last strategy therefore shows the best ratio of positive to negative trades but unfortunately, also the worst risk/return profile of all tested strategies.

Table XIII. Annualised performance statistics strategy 5

The table presents the annualised performance statistics from the backtest of strategy 5 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The annualised return, standard deviation, and Sharpe Ratio is shown for the benchmark and the portfolio built with strategy 5.

	Benchmark Return	Strategy Return
Annualized Return	0.1264	0.1584
Annualized Std Dev	0.1540	0.2044
Annualized Sharpe Ratio (RF = 0%)	0.8206	0.7750

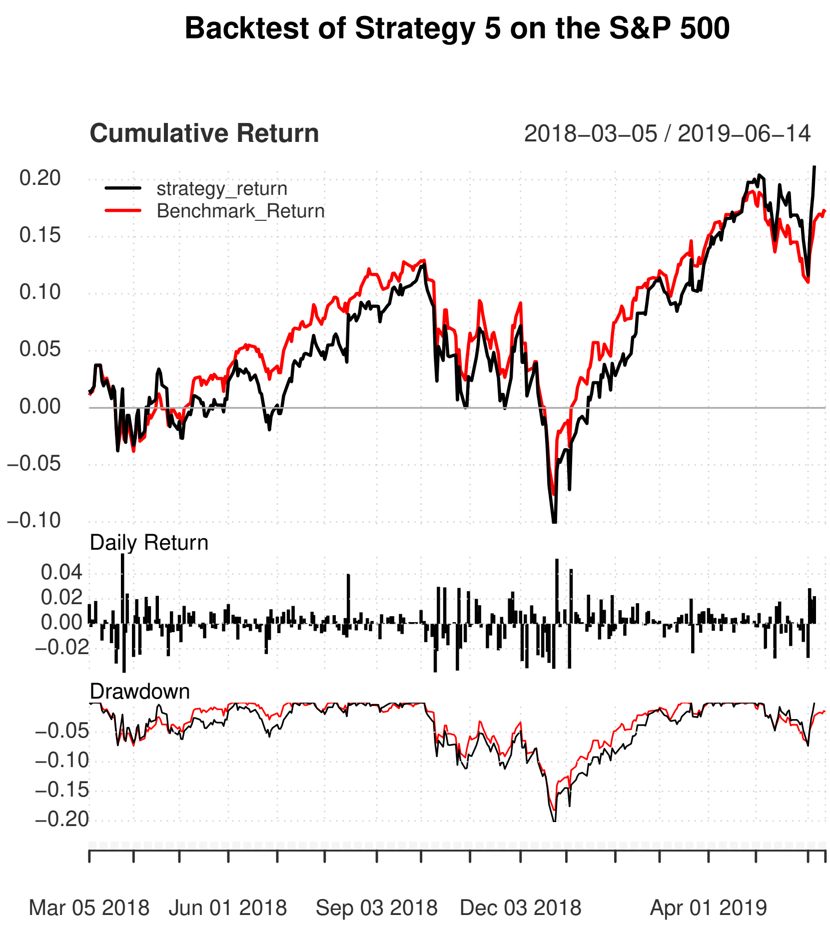

Figure 8. Backtest of Strategy 5 on the S&P 500

The figure presents the result of backtesting strategy 5 on the S&P 500 index from 05. March 2018 until 14. June 2019. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The first part of the figure shows the cumulative return of the benchmark (red) and the built portfolio (black). The second section shows the daily return of the portfolio and the third section the drawdowns of the portfolio and the benchmark.

In summary, in this subchapter, the author has developed five simple strategies based on the Sentifi data and tested them on the S&P 500 Index for the period from March 5, 2018, to June 14, 2019. Table XX in the appendix provides a brief overview of the five strategies. The strategies vary widely in terms of the number of trades executed, the ratio of positive to negative trades, holding period of shares, cumulative and annualized return, and Sharpe Ratio. All strategies have in common that they generate a higher return than the benchmark over the tested period, which could be a first indication that the Sentifi data can be used to generate excess returns. In the next chapter, it will be examined whether this excess return is equivalent to “Alpha”, or if they simply reflect more loadings on economic risk factors. In addition, the strategies developed are applied to other indices and tested in the form of an out-of-sample analysis.

5 Results

This section provides an in-depth presentation and analysis of the empirical outcome. Furthermore, some major and minor shortfalls are discussed. In the first step, the strategies developed in subsection 4.3 are applied to the indices SPI and Stoxx Europe 600, which serve as test sets in this paper. Then the portfolio returns are empirically examined to see if they are abnormal returns, and finally the shortcomings of the analysis are explained.

5.1 Backtest

After five strategies have been developed on the training dataset - the S&P 500 - the author decides not to pursue the two least promising strategies further. The three strategies that will continue to be considered were chosen for various reasons. Strategy 1 has the highest annualised return and the highest Sharpe Ratio, Strategy 4 has the least trades executed, and strategy 5 has the best ratio of positive to negative trades. In addition, all three strategies differ both in the derivation of the buy signal and in the rebalancing period.

These three strategies are applied to the respective indices to test whether they are also successful outside the training data set or whether the performance of the strategies on the S&P 500 is due to over-fitting. First, the three strategies were applied to the Stoxx Europe 600 index. Fortunately, all three strategies again achieved a higher cumulative return than the benchmark. While the annualized buy and hold return of the Stoxx Europe 600 Portfolio for the considered period is 12.36%, the three strategies based on the Sentifi data get an annualized return of 58.23%, 24.77%, and 26.46%. Furthermore, the annualized Sharpe Ratios of 2.5950, 1.8011 and 1.8142 at a risk-free rate of 0% imply that the tested strategies have better risk-adjusted returns than the benchmark with a Sharpe Ratio of 1.0455.

In addition, the three strategies confirmed their respective strengths, strategy 1 has the highest annualized and cumulative return, strategy 4 the lowest number of trades and the longest average holding period and strategy 5 the lowest proportion of trades with negative returns. Furthermore, it is noticeable that Strategy 5 has achieved a very strong performance and Sharpe Ratio over this period compared to the result of the strategy applied to the S&P 500 index. The trading statistics are summarized in Table XIV and the performance of the strategies is shown in detail in figure 9.

The next step is to apply the three strategies to the SPI. In the period under review, the SPI recorded a significantly higher return than the other two indices. That is why it is interesting to see that the strategies still outperform the benchmark, but the respective excess returns are significantly lower than before. Unfortunately, due to the short period of consideration in this thesis, no general statement can be made as to whether the strategies based on the Sentifi data are better suited to bear markets than bull markets. However, the results from this backtest could be a first indication, and this would be an exciting research topic for future work if data are available over a longer period of time.

Table XIV. Trading Statistics Backtest Stoxx Europe 600

The table presents the trading and performance statistics from the backtest of strategy 1, strategy 4, and strategy 5 on the Stoxx Europe 600 index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolio is rebalanced every day. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The annualised return, standard deviation, and Sharpe Ratio is shown for the benchmark and the portfolios built with the three strategies. Furthermore, the number of trades, the share of trades with negative performance and the average holding period is shown for each of the three strategies.

	Benchmark	Strategy 1	Strategy 4	Strategy 5
Annualized Return	0.1236	0.5823	0.2477	0.2646
Annualized Std Dev	0.1182	0.2244	0.1375	0.1458
Annualized Sharpe Ratio (RF = 0%)	1.0455	2.5950	1.8011	1.8142
Number of Trades	-	4950	81	426
Negative Trades (%)	-	46.53	45.68	43.66
Average Holding Period	-	2.34	60.70	9.02

Table XV. Trading Statistics SPI

The table presents the trading and performance statistics from the backtest of strategy 1, strategy 4, and strategy 5 on the SPI index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolio is rebalanced every day. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The annualised return, standard deviation, and Sharpe Ratio is shown for the benchmark and the portfolios built with the three strategies. Furthermore, the number of trades, the share of trades with negative performance and the average holding period is shown for each of the three strategies.

	Benchmark	Strategy 1	Strategy 4	Strategy 5
Annualized Return	0.1754	0.3747	0.2072	0.2485
Annualized Std Dev	0.1241	0.1988	0.1447	0.1356
Annualized Sharpe Ratio (RF = 0%)	1.4129	1.8853	1.4316	1.8327
Number of Trades	-	933	10	216
Negative Trades (%)	-	44.69	50	44.44
Average Holding Period	-	3.98	80.70	15.72

Nevertheless, the results again look promising that the strategies could work and the respective strengths of the strategies have been reaffirmed. As in the backtest on the Stoxx Europe 600, Strategy 5 can again convince with a high annualized return, a high Sharpe Ratio, a reasonable number of trades and the lowest percentage of negative trades. The trading statistics are summarized in Table XV and the performance of the strategies is shown in detail in figure 10.

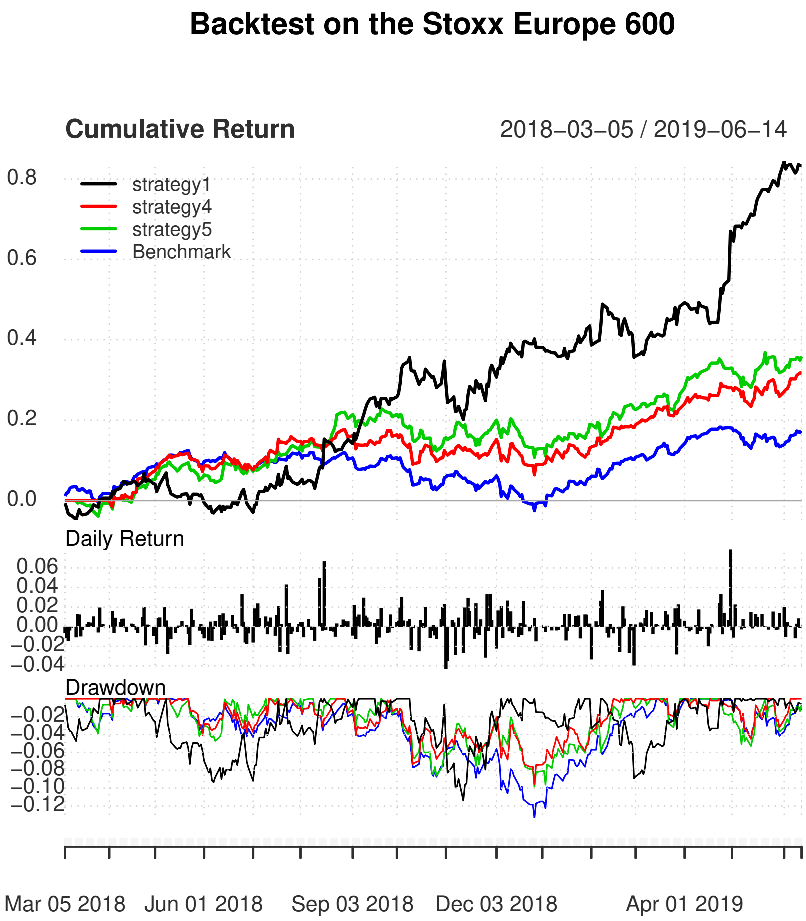

Figure 9. Backtest Stoxx Europe 600

The figure presents the result of backtesting strategy 1, strategy 4, and strategy 5 on the Stoxx Europe 600 index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolio is rebalanced every day. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The first part of the figure shows the cumulative return of the benchmark (blue), strategy 1 (black), strategy 4 (red), and strategy 5 (green). The second section shows the daily return of strategy 1 and the third section the drawdowns of each portfolio and the benchmark.

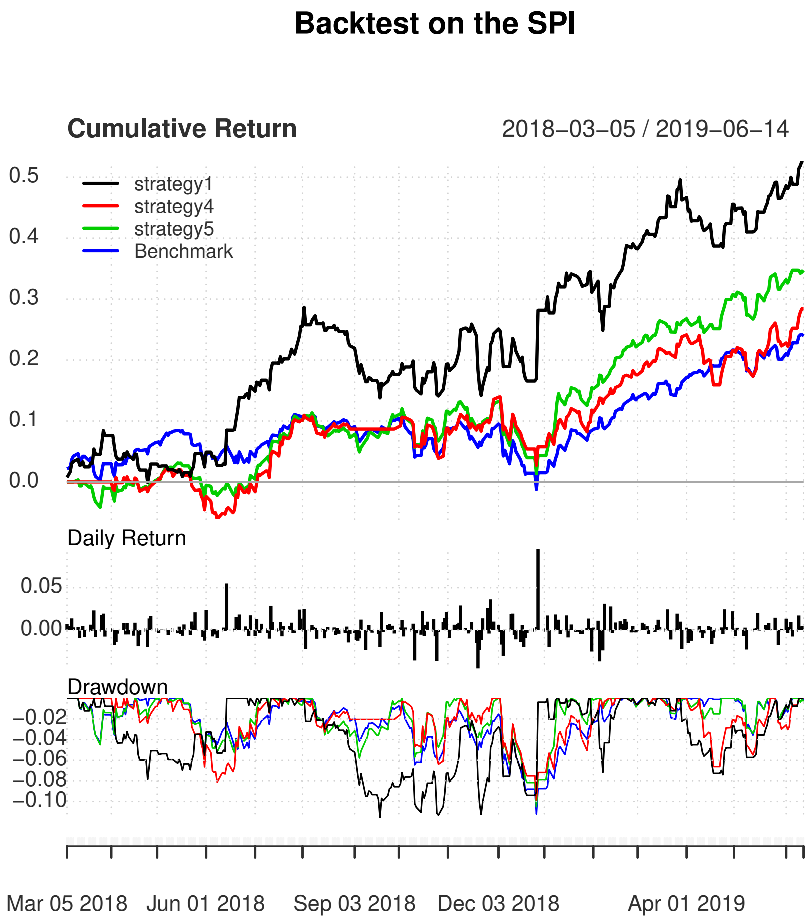

Figure 10. **Backtest SPI**

The figure presents the result of backtesting strategy 1, strategy 4, and strategy 5 on the SPI index from 05. March 2018 until 14. June 2019. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolio is rebalanced every day. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolio is rebalanced weekly. The first part of the figure shows the cumulative return of the benchmark (blue), strategy 1 (black), strategy 4 (red), and strategy 5 (green). The second section shows the daily returns of strategy 1 and the third section the drawdowns of each portfolio and the benchmark.

The backtests have shown that the three strategies tested have led to an excess return on all indices. This strengthens the belief that it is possible to use the Sentifi data to predict the development of share prices to a certain degree.
It remains to be tested, whether the sentiment data provide an abnormal return or simply reflect more loadings on economic risk factors. This will be discussed in the next subchapter.

5.2 Abnormal Returns

As described in detail in subchapter 4.2, the author estimates the time-series regression (equation 9) based on the Fama and French (2015) five-factor model expanded by the momentum factor proposed by Carhart (1997) to evaluate the return performance. Furthermore, other established asset pricing models such as the CAPM and the Fama and French (1993) three-factor Model and Fama and French (2015) five-factor model are considered to check the robustness of the model. A similar approach was followed by Breitmayer, Pelster, and Massari (2016) and Hong and Kacperczyk (2009).

When dealing with time-series regression, coefficients are usually estimated with the least-squares algorithm, which assumes an error term with zero expectation, constant variation, and no correlation. But since time-series predictors and response are usually autocorrelated, the last condition often turns out to be violated. Even if the coefficients remain unbiased, this leads to completely wrong standard errors, which are mostly underestimated, resulting in spurious significance. To find out if the errors are correlated, uncorrelated errors are assumed first, and an ordinary least squares regression is performed. Based on this regression, it can be verified if the errors are correlated and if so, actions can be taken. In this thesis, the Durbin-Watson test is used for this purpose. It tests the null hypothesis that the errors are uncorrelated against the alternative that the errors are correlated (Durbin and Watson (1951)). The Durbin-Watson test clearly shows that correlated errors are present in all of the time-series regressions performed in this thesis. To account for this issue, the standard errors are adjusted using the Newey-West correction from Newey and West (1987).

Table XVI presents the results obtained from the mentioned time-series regressions on returns on the five in subsection 4.3 developed strategies. The dependent variable is the strategy return minus the risk-free rate, and each regression is estimated with the daily data over the sample period from 5 March to 30 April 2019. Note that the sample period for calculating the abnormal returns is slightly shorter than for the backtest, as the Fama French data is only available until April 30, 2019. In a first step, we evaluate the outcome of running the strategies on the S&P 500. What is particularly interesting about the regression is the constant term that represents the alpha of the portfolios created based on the developed strategies. The constant term shows a positive alpha for all five tested strategies. But since only the constants of strategies 1 and 2 are significant at the 1% level and strategy 4 is significant at the 10% level, we can only speak of a generated alpha for these three strategies. While strategy 1 generates an abnormal return of 0.3% over the observed period, strategy 2 generates 0.04%, and strategy 4 generates 0.03%. If we remember that transaction costs have not been taken into account and that the strategies sometimes cause a large number of trades, these abnormal returns are put into perspective. To assess whether the results for the alpha are driven by a particular regression model, the other regression models (equation 4 - 7) were also run. The results can be found in the appendix (table XXI - XXV). The alphas from the CAPM, Fama and French (1993) three-factor model and Fama and French (2015) five-factor model are very similar for strategy 1, 2 and 4.
Interesting to point out is the negative and highly significant coefficients for the SMB factor in

the strategies 2 - 5. This implies that in the portfolios created with these strategies, there is a greater exposer in equities with large market capitalization than in equities with small market capitalization. Furthermore, the coefficient of the market premium factor in strategies 2 - 5 is relatively close to 1 and also highly significant.

Table XVI. Fama-French 5-Factor model expanded by Momentum Factor

The table reports coefficients obtained from the time-series regression $R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$ on returns of five different portfolios. The portfolios are created by applying five different strategies based on sentiment data from Sentifi on the S&P 500 index. These are explained in detail in the Appendix in table XX. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction. The dependent variable in model (1) is the portfolio return obtained with strategy 1 minus the risk-free interest rate, model (2) is that obtained with strategy 2, model (3) is that obtained with strategy 3, model (4) is that obtained with strategy 4 and model (5) is the one obtained with strategy (5).

	Dependent variable:				
	Strategy Return - RF				
	(1)	(2)	(3)	(4)	(5)
Constant (Alpha)	0.003^{***}	0.0004^{***}	0.0005	0.0003^{*}	0.0002
	(0.001)	(0.0001)	(0.0004)	(0.0002)	(0.0003)
MktRF	0.087	0.999^{***}	1.051^{***}	1.111^{***}	1.128^{***}
	(0.104)	(0.016)	(0.055)	(0.024)	(0.046)
SMB	0.142	-0.150^{***}	-0.210^{***}	-0.220^{***}	-0.273^{***}
	(0.236)	(0.023)	(0.062)	(0.047)	(0.061)
HML	−0.119	0.026	−0.063	-0.165^{**}	−0.098
	(0.229)	(0.039)	(0.103)	(0.072)	(0.097)
RMW	−0.176	0.047	0.116	0.067	0.044
	(0.300)	(0.031)	(0.116)	(0.057)	(0.088)
CMA	0.420	0.014	0.138	-0.272^{***}	0.072
	(0.403)	(0.041)	(0.171)	(0.103)	(0.155)
Mom	0.143	0.0001	0.312^{**}	0.307^{***}	0.292^{***}
	(0.203)	(0.027)	(0.134)	(0.052)	(0.082)
Observations:	290	252	286	272	291
Note:			*p<0.1; **p<0.05; ***p<0.01		

In the next step, the same regressions are applied to the strategy returns of strategies 1, 4 and 5 for the Stoxx Europe 600 and the SPI. The results are shown in Tables XVII (for the Stoxx Europe 600) and XVIII (for the SPI). For all three strategies the Fama and French (2015) five-factor Model with additional Momentum factor as well as the CAPM, the Fama and French (1993) three-factor Model and the Fama and French (2015) five-factor Model are listed. The latter three models serve as robustness tests.

Table XVII. Regression Result Stoxx Europe 600

The table reports coefficients obtained from the four following time-series regression on returns of three different portfolios.

$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$

$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$

$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$

$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$

The portfolios are created by applying strategies 1, 4 and 5 based on sentiment data from Sentifi on the Stoxx Europe 600 index. These three strategies are explained in detail in the Appendix in table XX. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction. The dependent variable in models (1) to (4) is the portfolio return obtained with strategy 1 minus the risk-free interest rate, model (5) to (8) is that obtained with strategy 4, model (9) to (12) is the one obtained with strategy 5.

	Dependent variable:											
	Strategy Return - RF											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant (Alpha)	0.002^{**}	0.001	0.001^{*}	0.001^{*}	0.001^{**}	0.0005	0.001^{*}	0.001^{*}	0.001^{**}	0.001^{*}	0.001^{*}	0.001^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
MktRF	-0.205^{*}	-0.250^{*}	-0.179	-0.127	0.711^{***}	0.597^{***}	0.694^{***}	0.719^{***}	0.772^{***}	0.670^{***}	0.699^{***}	0.707^{***}
	(0.124)	(0.131)	(0.130)	(0.131)	(0.061)	(0.064)	(0.057)	(0.054)	(0.040)	(0.046)	(0.049)	(0.050)
SMB		-0.397	-0.345	-0.344		-0.823^{***}	-0.799^{***}	-0.779^{***}		-0.727^{***}	-0.731^{***}	-0.730^{***}
		(0.291)	(0.283)	(0.279)		(0.152)	(0.133)	(0.127)		(0.126)	(0.120)	(0.122)
HML		-0.938^{***}	-1.343^{***}	-0.927^{**}		-0.470^{***}	-1.357^{***}	-1.183^{***}		-0.262^{*}	-0.621^{***}	-0.557^{***}
		(0.229)	(0.429)	(0.449)		(0.111)	(0.163)	(0.162)		(0.134)	(0.172)	(0.181)
RMW			0.032	-0.099			-0.866^{***}	-0.915^{***}			-0.441^{*}	-0.457^{*}
			(0.592)	(0.593)			(0.206)	(0.198)			(0.265)	(0.264)
CMA			0.924	0.348			1.016^{***}	0.796^{***}			0.307	0.223
			(0.595)	(0.618)			(0.219)	(0.211)			(0.218)	(0.222)
Mom				0.675^{***}				0.256^{***}				0.099
				(0.225)				(0.072)				(0.089)
Observations:	301	301	301	301	282	282	282	282	297	297	297	297

Note: *p<0.1; **p<0.05; ***p<0.01

Table XVIII. Regression Results SPI

The table reports coefficients obtained from the four following time-series regression on returns of three different portfolios.
$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$
$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$
$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$
$R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$
The portfolios are created by applying strategies 1, 4 and 5 based on sentiment data from Sentifi on the SPI. These three strategies are explained in detail in the Appendix in table XX. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction. The dependent variable in models (1) to (4) is the portfolio return obtained with strategy 1 minus the risk-free interest rate, model (5) to (8) is that obtained with strategy 4, model (9) to (12) is that obtained with strategy 5.

	Dependent variable: Strategy Return - RF											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant (Alpha)	0.001*	0.001	0.001*	0.001*	0.001	0.0003	0.0005	0.0005	0.001**	0.001	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
MktRF	0.424***	0.403**	0.536***	0.544***	0.570***	0.459***	0.642***	0.668***	0.672***	0.592***	0.700***	0.710***
	(0.159)	(0.181)	(0.192)	(0.194)	(0.081)	(0.084)	(0.079)	(0.079)	(0.056)	(0.063)	(0.069)	(0.063)
SMB		−0.185	−0.199	−0.204		−0.816***	−0.800***	−0.784***		−0.599***	−0.593***	−0.591***
		(0.462)	(0.426)	(0.417)		(0.197)	(0.164)	(0.164)		(0.207)	(0.197)	(0.171)
HML		−0.503*	−1.822***	−1.757***		−0.430**	−2.122***	−1.934***		−0.491***	−1.640***	−1.562***
		(0.261)	(0.373)	(0.390)		(0.185)	(0.241)	(0.237)		(0.137)	(0.168)	(0.177)
RMW			−1.359***	−1.380***			−1.670***	−1.733***			−1.236***	−1.256***
			(0.515)	(0.523)			(0.323)	(0.303)			(0.238)	(0.242)
CMA			1.428**	1.338**			1.886***	1.633***			1.174***	1.070***
			(0.566)	(0.581)			(0.356)	(0.358)			(0.276)	(0.276)
Mom				0.105				0.286***				0.123
				(0.176)				(0.108)				(0.090)
Observations:	264	264	264	264	262	262	262	262	297	297	297	297

Note: *p<0.1; **p<0.05; ***p<0.01

For the Stoxx Europe 600 index, all three tested strategies generate significant and positive alpha. Strategy 1, as well as strategies 4 and 5, show an abnormal return of 0.1% which is significant at the 10% level. These alphas are also confirmed by the other models, which each have an identical or similar constant term. What is interesting is that the coefficient for the market risk premium is well below one and highly significant. This means that the portfolios created have a lower systematic risk exposure than the market.

Looking at the regression results for the SPI, it can be seen that all three strategies generate a positive alpha again. However, the constant term of the fourth strategy is not significant. The first strategy again generates an alpha of 0.1% which is significant at the 10% level and the fifth strategy generates an alpha of 0.1% which is significant at the 5% level. Again, these alphas are confirmed by the other models, which each have an identical or similar constant term. And just like the Stoxx Europe 600 index, the coefficient of the market risk premium indicates that the portfolios created have a lower systematic risk exposure than the market.

In conclusion, it can be stated that this thesis was able to empirically confirm the potential of Sentifi's sentiment data in order to generate excess return. A long/short strategy - strategy 1 - based on the Sentifi Sentiment-Score and Attention-Buzz data generated a positive and significant alpha on the S&P 500, the Stoxx Europe 600 and the SPI Index. Furthermore, other strategies have also generated a positive significant alpha on various indices. In order to close this chapter, the following subchapter will deal with certain shortfalls and further research possibilities.

5.3 Shortfalls and further Studies

The first thing to point out in this subsection are the transaction costs. As already mentioned several times, the transaction costs have not been considered when testing the strategies. Nevertheless, since certain strategies involve a large number of trades, high transaction costs may be incurred. However, since a well-founded estimate of transaction costs was not found in the considered literature and a separate estimate would exceed the scope of this thesis, the approach of Breitmayer, Pelster, and Massari (2016) is applied and no transaction costs are calculated. It is important to note that the direct implementation of the developed strategies will cause costs.

The second major shortfall of this thesis is that the observation time is very short. The data covers only a period where the economic structure has been generally positive and the markets rising. Therefore, it is not possible to say how the strategies work in different economic cycles. This offers the potential for further studies once the database is larger and comprises several years. Furthermore, this thesis should be a first example to prove that it is possible to generate an excess return with the data provided by Sentifi. The possibilities that the "Sentifi engine" will offer in the future and already offers today go much further than the data used in this thesis. These possibilities allow us to develop even more sophisticated strategies that could lead to an even greater and more reliable excess return.

An example of this would be if the data of the event recognition tool were included in the strategy. Depending on the type of event that triggers the high Sentiment-Score and high attention, a buy signal could be triggered or not. Another possibility would be to make the holding period of the stock dependent on the event. If the high Sentiment-Score is triggered by an event that promises sustainably higher returns, this should lead to a longer holding period for the stock and it should not be sold again as soon as the Sentiment-Score falls. Furthermore, the “Sentifi Engine” is capable of delivering intraday data since the Sentiment-Score is updated every 15 minutes. Analysing this might be interesting for day traders and could offer additional potential for an excess return.
In another study, the idea of Leinweber and Sisk (2011) could also be implemented. They suggest to implement a metric for a surprise sentiment which then looks at strong Sentiment-Scores of a company that differ from the Sentiment-Scores of companies in its peer group and build a strategy based on this metric (Leinweber and Sisk (2011)).

The sentiment data should also not be viewed in isolation. A professional portfolio manager would integrate the sentiment data in his arsenal of other information sources and investment ideas. For example, the present thesis could be supplemented in a further paper by volatility and trading volume analytics.

In the development of the strategies in this thesis, the implicit assumption was made that all companies react equally sensitively to investor sentiment. However, Baker and Wurgler (2007) found that younger, smaller, more volatile, unprofitable, non-dividend paying, distressed, or companies with extreme growth potential are the most sensitive to investor sentiment. On the other hand, stocks with bond similar characteristics are less influenced by investor sentiment. These company-specific characteristics could be incorporated into the strategies in further work, as well as information on the industry and the sector.

This thesis has shown that it is possible to generate alpha using collective financial intelligence provided by Sentifi. Still, from what we have seen, not all possibilities of the “Sentifi Engine” have been explored yet and the field offers many research opportunities as soon as data over a longer period of time becomes more readily available.

6 Conclusion

This thesis investigates whether it is possible to generate alpha with collective financial intelligence provided by Sentifi. The Sentifi Engine uses a combination of supervised and unsupervised learning to score the financial relevance published by a source and the source itself and calculates the Sentiment-Score, which indicates the crowd sentiment towards an asset.
The author has developed strategies based on this Sentiment-Score and the Attention-Buzz - a measure that indicates a company's above-average attention - to show that sentiment data provided by Sentifi can predict stock prices to a certain extent. Results show that all strategies applied to the stocks of the S&P 500 index outperform the benchmark in a backtest over the observation period from March 5, 2018, to June 14, 2019.
Three promising strategies were then selected and applied to Stoxx Europe 600 and SPI stocks. The portfolios formed in this way also performed better than the respective benchmarks in a backtest.

The executed Time Series regressions have proven that it is possible to generate an abnormal return with Sentifi's sentiment data, which doesn't just reflect more loadings on the economic risk factors. A long/short strategy - strategy 1 - based on the Sentifi Sentiment-Score and Attention-Buzz data generated a positive and significant alpha on the S&P 500, the Stoxx Europe 600 and the SPI Index between 0.1 % (SPI & Stoxx Europe 600) and 0.3% (S&P 500) over the observed period. Furthermore, other strategies have also generated a positive significant alpha on various indices. These results confirm the hypothesis initially formulated and further imply that the semi-strong form of the efficient market hypothesis is not given.

However, this result must take into account that the study deals with major and minor shortfalls. In particular, the transaction costs not taken into account, and the short observation period must be mentioned here. The transaction costs incurred would reduce the alpha generated to a large extent or eliminate it completely. Also, due to the short observation period, it is not possible to estimate how the strategies will perform in different economic cycles.
These shortcomings, combined with the great possibilities that the Sentifi Engine offers and will continue to offer in the future, provide the opportunity for further studies in this field. Especially the Sentifi event recognition tool and the combination of sentiment data and other trading relevant information, such as volatility analytics, allow for the development and testing of additional exciting strategies, which are left to further research.

7 References

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Appendix A: Appendix

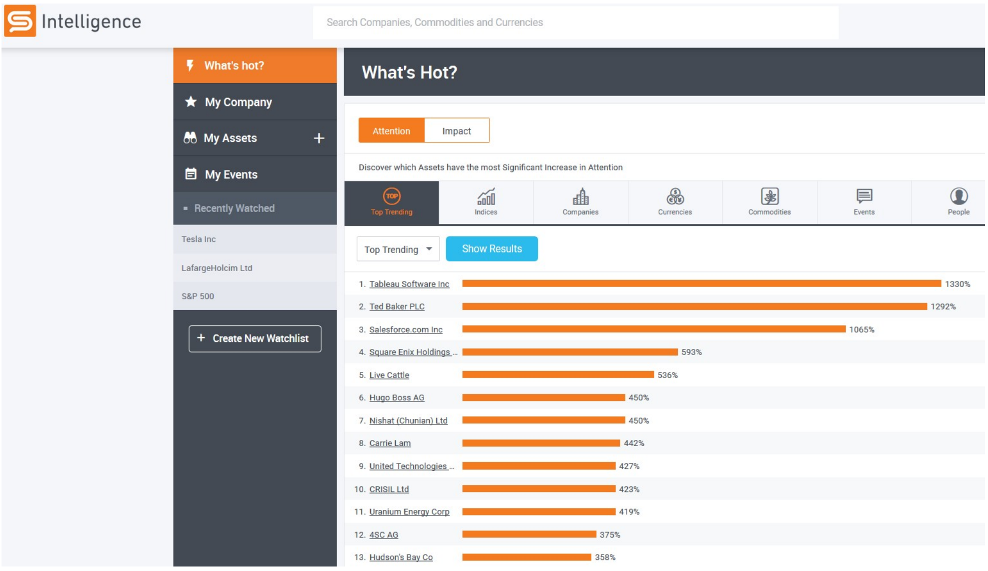

Figure 11. Welcome page of Sentifi Intelligence

The figure shows the front page of the Sentifi Intelligence Welcome page. Sentifi Intelligence reports the indices, currencies, companies, people, commodities and events that get the most attention over a certain period. Furthermore, it is possible to save companies, assets and event types on watchlists. Source: Sentifi (2019b)

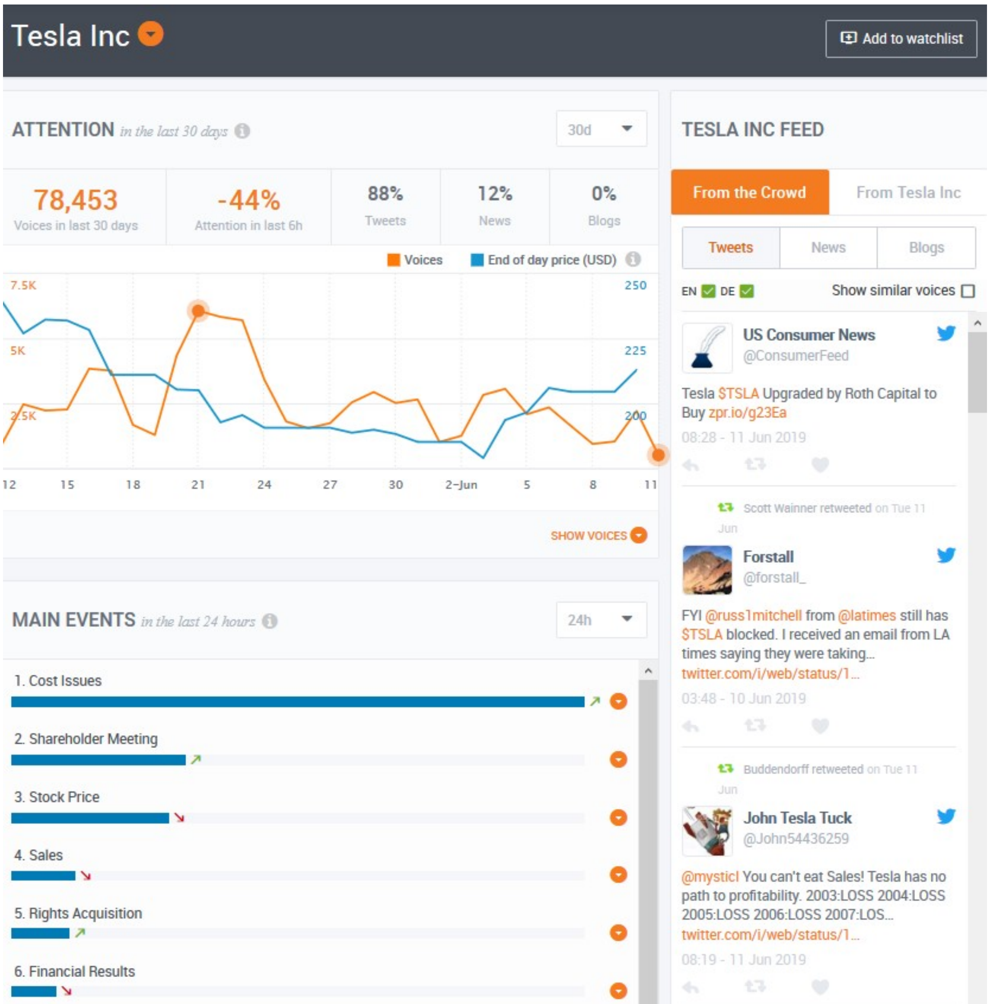

Figure 12. **Instrument page of Sentifi Intelligence**

The figure shows an example of an instrument specific page on Sentifi Intelligence. On this page, Sentifi reports the absolute number of voices, relative change of attention and a chart that compares the number of voices to the end of day price. On the right-hand side there is the company's news feed and the top-ranked influencers can be found at the bottom of the page. Source: Sentifi (2019b)

Table XIX. Example excerpt of dataset

The table provides an example excerpt of the dataset used in this thesis. An observation contains the variables date, weekday, name, ISIN, Blomberg Ticker (Ticker), sector, industry, daily Sentiment-Score (sent score), Attention-Volume (attn vol), Attention-Buzz (attn buzz), lag(Sentiment-Score), lag(Attention-buzz), Sentiment-Label (label), total return (Return), market capitalization (MC), the five Fama-French factors (MktRF, SMB, HML, RMW , CMA), the risk free rate (RF) and the momentum factor (Mom). Both the ISIN number and the Bloomberg ticker act as unique identifiers.

date	weekday	legalname	isin	Ticker	sector	industry	sent_score	attn_vol	attn_buzz	sent_score_lag	attn_buzz_lag	Return	MC	MktRF	SMB	HML	RMW	CMA	RF	Mom
17648	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	6.538461538	250	22.63636364	14.64285714	24.45454545	-0.00172474428140645	91996.9433	1e-04	-0.0027	7e-04	0.0062	9e-04	7e-05	0.003
17649	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	17.85714286	102	9.181818182	6.538461538	22.63636364	NA	NA	NA	NA	NA	NA	NA	NA	NA
17650	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	25.86206897	222	20.09090909	17.85714286	9.181818182	NA	NA	NA	NA	NA	NA	NA	NA	NA
17651	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	50.73409462	603	54.72727273	25.86206897	20.09090909	-0.00462662793966084	91571.1958	-0.008	-6e-04	-8e-04	-0.0048	-2e-04	7e-05	0.0028
17652	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	37.2745491	489	44.36363636	50.73409462	54.72727273	0.00368047802914639	91908.2459	0.0024	0.0025	-0.0053	0	-0.0095	6e-05	0.0036
17653	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	9.763313609	328	29.72727273	37.2745491	44.36363636	-0.00212328561567776	91713.1116	-0.0063	0.0124	-0.0028	0	-2e-04	6e-05	0.0041
17654	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-19.18604651	506	45.90909091	9.763313609	29.72727273	-0.011992391034654	90613.2638	-0.0025	-0.0058	-0.0017	0	-0.001	6e-05	0.0086
17655	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-1.388888889	350	31.72727273	-19.18604651	45.90909091	0.00626493463007782	90991.364	0.013	-3e-04	-0.0023	-0.0037	6e-04	6e-05	-0.0044
17656	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	10.36585366	154	13.90909091	-1.388888889	31.72727273	NA	NA	NA	NA	NA	NA	NA	NA	NA
17657	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-4.545454545	144	13	10.36585366	13.90909091	NA	NA	NA	NA	NA	NA	NA	NA	NA
17658	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	29.46058091	231	20.90909091	-4.545454545	13	0.0192601107546175	92743.9214	0.0042	0.0038	-0.0036	-0.0052	-0.0032	6e-05	0.0029
17659	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	25	286	25.90909091	29.46058091	20.90909091	0.0188961684572919	94496.4788	7e-04	0.005	0.0026	-0.0026	0.0014	6e-05	0.0044
17660	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	8.737864078	196	17.72727273	25	25.90909091	0.0142383545333895	95841.8764	0.0089	-0.0023	0.0024	-0.0089	0	6e-05	0.003
17661	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	13.49862259	353	32	8.737864078	17.72727273	0.0166232283634171	97435.1104	0.0084	-0.0037	-4e-04	0.0025	-0.0033	6e-05	-0.0016
17662	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-5.755395683	268	24.27272727	13.49862259	32	0.00290797760486461	97718.352	0.0019	0.0011	-0.0037	0.002	0.0013	6e-05	0.0017
17663	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-3.361344538	109	9.818181818	-5.755395683	24.27272727	NA	NA	NA	NA	NA	NA	NA	NA	NA
17664	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	7.258064516	114	10.27272727	-3.361344538	9.818181818	NA	NA	NA	NA	NA	NA	NA	NA	NA
17665	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	34.96503497	419	38	7.258064516	10.27272727	0.000360902785113248	97753.7572	5e-04	-0.0029	0.0011	-0.0018	0.0051	6e-05	-0.0038
17666	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	18.57923497	356	32.27272727	34.96503497	38	-0.00669981081437809	97098.761	-0.0055	0.0071	0.0041	-7e-04	0.0043	6e-05	-6e-04
17667	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	7.306590258	688	62.45454545	18.57923497	32.27272727	0.00218809463907954	97311.1922	0.0049	0.0068	-0.0024	0.0036	0.001	6e-05	-2e-04
17668	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	12.00828157	956	86.81818182	7.306590258	62.45454545	-0.00181913646705667	97134.1662	2e-04	0.0087	0.0025	-0.0032	0.003	6e-05	0.0021
17669	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	6.510416667	374	33.90909091	12.00828157	86.81818182	-0.0173141772223639	95452.4192	-0.0023	0.0046	-0.0058	6e-04	-0.002	6e-05	0.0064
17670	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	1.851851852	152	13.72727273	6.510416667	33.90909091	NA	NA	NA	NA	NA	NA	NA	NA	NA
17671	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	10.27027027	175	15.81818182	1.851851852	13.72727273	NA	NA	NA	NA	NA	NA	NA	NA	NA
17672	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	24.41471572	289	26.18181818	10.27027027	15.81818182	0.00816079358671207	96231.3336	0.0072	-0.0019	0.0043	0.0018	7e-04	6e-05	0.0025
17673	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	25.74257426	495	44.90909091	24.41471572	26.18181818	0.00956601641829469	97151.8688	-0.0042	-0.0066	0.0059	-0.0029	-0.0039	6e-05	-0.0021
17674	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	22.84263959	384	34.81818182	25.74257426	44.90909091	-0.00965776383987305	96213.631	0.0029	-7e-04	-0.0071	-4e-04	-0.0037	6e-05	0.0043
17675	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	14.87964989	447	40.54545455	22.84263959	34.81818182	-0.00644050401145768	95594.04	-0.0016	0.0032	-0.0031	0.0049	9e-04	6e-05	0.0013
17676	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	21.21212121	221	20	14.87964989	40.54545455	-0.0183327904461453	93841.4826	-0.0021	0.0022	-0.004	0.006	-0.0053	6e-05	-0.0056
17677	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	20	75	6.727272727	21.21212121	20	NA	NA	NA	NA	NA	NA	NA	NA	NA
17678	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-13.7254902	41	3.636363636	20	6.727272727	NA	NA	NA	NA	NA	NA	NA	NA	NA
17679	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	22.5	70	6.272727273	-13.7254902	3.636363636	0	93841.4826	NA	NA	NA	NA	NA	NA	NA
17680	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	11.87384045	529	48	22.5	6.272727273	-0.0575360597194419	88442.1896	-0.0103	0.011	-0.0103	0.0018	-3e-04	6e-05	-8e-04
17681	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	6.402439024	318	28.81818182	11.87384045	48	0.020215950624296	90230.1522	0.0131	4e-04	0.0035	-0.007	0.002	6e-05	0.0027
17682	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-7.050092764	529	48	6.402439024	28.81818182	-0.0162843284549621	88760.8364	-0.007	4e-04	-0.004	-0.0052	-0.0016	6e-05	0.0037
17683	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	0	308	27.90909091	-7.050092764	48	0.0213411738711622	90655.0146	0.0106	-0.0021	-0.0013	-2e-04	-0.0017	6e-05	0.0058
17684	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	17.07317073	113	10.18181818	0	27.90909091	NA	NA	NA	NA	NA	NA	NA	NA	NA
17685	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	28.125	86	7.727272727	17.07317073	10.18181818	NA	NA	NA	NA	NA	NA	NA	NA	NA
17686	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	13.33333333	215	19.45454545	28.125	7.727272727	0.00663804980245253	91256.903	0.0048	0.0015	-0.0046	0.0103	-0.0029	6e-05	0.0016
17687	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	11.6	240	21.72727273	13.33333333	19.45454545	-0.0149360932021264	89893.8028	0.0016	0.0079	-0.0041	0.0021	0.0012	6e-05	0.0029
17688	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	18.84422111	388	35.18181818	11.6	21.72727273	0.0222529696461686	91894.1966	0.0086	-0.0028	0.0017	-2e-04	0.0015	6e-05	-1e-04
17689	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	21.91358025	314	28.45454545	18.84422111	35.18181818	0.00443121507399402	92301.3564	-0.0014	-0.0024	0.0092	0.0013	0.0059	6e-05	-0.0091
17690	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	13.59223301	196	17.72727273	21.91358025	28.45454545	-0.00441166603296728	91894.1966	0.0031	5e-04	-0.004	0.0024	-0.0019	6e-05	-0.0013
17691	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	24.24242424	56	5	13.59223301	17.72727273	NA	NA	NA	NA	NA	NA	NA	NA	NA
17692	Sunday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	4.081632653	137	12.36363636	24.24242424	5	NA	NA	NA	NA	NA	NA	NA	NA	NA
17693	Monday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	12.14285714	270	24.45454545	4.081632653	12.36363636	-0.00250484400887363	91664.0628	0.0012	0.0015	-0.0016	0.0023	0.0024	6e-05	-0.0063
17694	Tuesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	38.23529412	364	33	12.14285714	24.45454545	-0.0088828081159551	90849.7432	0.0023	0.0019	-0.0061	8e-04	-0.0017	6e-05	0.0016
17695	Wednesday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	17.43295019	512	46.45454545	38.23529412	33	0.00545546815529052	91345.416	-0.0033	5e-04	-0.0021	-0.0048	-0.0016	6e-05	0.0022
17696	Thursday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	4.029304029	263	23.81818182	17.43295019	46.45454545	-0.00561985027543654	90832.0406	0.0027	0.002	-0.0099	0	-0.0059	6e-05	-0.0023
17697	Friday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	-6.801007557	387	35.09090909	4.029304029	23.81818182	-0.00292429227013347	90566.5016	-8e-04	0.0011	-0.0024	0.0065	-0.0015	6e-05	-0.0089
17698	Saturday	Morgan Stanley	US6174464486	MS UN Equity	Financial Services	Capital Markets	16.41791045	124	11.18181818	-6.801007557	35.09090909	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table XX. Strategies

The table presents the five in subsection 4.3 developed strategies and a brief description of every strategy.

Strategy	Explanation
Strategy 1	A long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore only stocks with an above average previous day Attention-Buzz are considered. The portfolios are rebalanced every day.
Strategy 2	A moving average strategy where stocks will be bought as soon as the 10 trading day moving average crosses the 40 trading day moving average from below, and sold as soon as the 10 trading day moving average crosses the 40 trading day moving average from above. The portfolio is rebalanced every day.
Strategy 3	A long strategy where a stock will be bought if the average Sentiment-Score of the previous week is at least 33. In addition, only stocks with an above average previous week average Attention-Buzz are considered. The portfolio is rebalanced every Monday.
Strategy 4	A long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly.
Strategy 5	A long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolios is rebalanced weekly.

Table XXI. Time Series Regression Analysis Strategy 1 S&P 500

The table reports coefficients obtained from the four following time-series regressions on returns of the portfolio built with strategy 1.

$(1) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$

$(2) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$

$(3) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$

$(4) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$

The portfolios are created by applying strategy 1 on the S&P 500 index. Strategy 1 is a long/short strategy where a long position in stocks with a previous day Sentiment-Score of at least 33 and a short position in stocks with a previous day Sentiment-Score of -33 or lower is taken. Furthermore, only stocks with an above-average previous day Attention-Buzz are considered. The portfolios are rebalanced every day. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction.

	Dependent variable:			
	Strategy Return - RF			
	(1)	(2)	(3)	(4)
Constant	0.003^{***}	0.003^{***}	0.002^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
MktRF	0.061	0.043	0.083	0.087
	(0.079)	(0.091)	(0.111)	(0.104)
SMB		0.114	0.097	0.142
		(0.233)	(0.236)	(0.236)
HML		−0.056	−0.206	−0.119
		(0.195)	(0.193)	(0.229)
RMW			−0.219	−0.176
			(0.262)	(0.300)
CMA			0.414	0.420
			(0.410)	(0.403)
Mom				0.143
				(0.203)
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table XXII. Time Series Regression Analysis Strategy 2 S&P 500

The table reports coefficients obtained from the four following time-series regressions on returns of the portfolio built with strategy 2.
$(1) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$
$(2) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$
$(3) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$
$(4) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$
The portfolios are created by applying strategy 2 on the S&P 500 index. Strategy 2 is a moving average strategy where stocks will be bought as soon as the 10 trading day moving average crosses the 40 trading day moving average from below, and sold as soon as the 10 trading day moving average crosses the 40 trading day moving average from above. The portfolio is rebalanced every day. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction.

	Dependent variable:			
	Strategy Return - RF			
	(1)	(2)	(3)	(4)
Alpha	0.0004^{***}	0.0004^{***}	0.0004^{***}	0.0004^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
MktRF	0.976^{***}	0.994^{***}	0.999^{***}	0.999^{***}
	(0.015)	(0.014)	(0.015)	(0.016)
SMB		-0.155^{***}	-0.150^{***}	-0.150^{***}
		(0.022)	(0.024)	(0.023)
HML		0.029	0.025	0.026
		(0.027)	(0.028)	(0.039)
RMW			0.047	0.047
			(0.030)	(0.031)
CMA			0.014	0.014
			(0.043)	(0.041)
Mom				0.0001
				(0.027)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table XXIII. Time Series Regression Analysis Strategy 3 S&P 500

The table reports coefficients obtained from the four following time-series regressions on returns of the portfolio built with strategy 3.
$(1) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$
$(2) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$
$(3) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$
$(4) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$
The portfolios are created by applying strategy 3 on the S&P 500 index. Strategy 3 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous week is at least 33. In addition, only stocks with an above-average previous week average Attention-Buzz are considered. The portfolio is rebalanced every Monday. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction.

	Dependent variable:			
	Strategy Return - RF			
	(1)	(2)	(3)	(4)
Alpha	0.001	0.0004	0.0003	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
MktRF	1.063***	1.024***	1.041***	1.051***
	(0.051)	(0.056)	(0.056)	(0.055)
SMB		−0.317***	−0.315***	−0.210***
		(0.082)	(0.080)	(0.062)
HML		−0.209***	−0.251**	−0.063
		(0.078)	(0.102)	(0.103)
RMW			0.018	0.116
			(0.095)	(0.116)
CMA			0.123	0.138
			(0.177)	(0.171)
Mom				0.312**
				(0.134)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table XXIV. Time Series Regression Analysis Strategy 4 S&P 500

The table reports coefficients obtained from the four following time-series regressions on returns of the portfolio built with strategy 4.

$(1) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$

$(2) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$

$(3) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$

$(4) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$

The portfolios are created by applying strategy 4 on the S&P 500 index. Strategy 4 is a long strategy where a stock will be bought if the average Sentiment-Score of the previous month is at least 33. In addition, only stocks with an above-average previous month average Attention-Buzz are considered. The portfolio is rebalanced monthly. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction.

	Dependent variable:			
	Strategy Return - RF			
	(1)	(2)	(3)	(4)
Alpha	0.0004	0.0001	0.0002	0.0003^{*}
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
MktRF	1.233^{***}	1.129^{***}	1.091^{***}	1.111^{***}
	(0.031)	(0.025)	(0.025)	(0.024)
SMB		-0.310^{***}	-0.316^{***}	-0.220^{***}
		(0.046)	(0.049)	(0.047)
HML		-0.454^{***}	-0.360^{***}	-0.165^{**}
		(0.051)	(0.061)	(0.072)
RMW			-0.025	0.067
			(0.075)	(0.057)
CMA			-0.274^{***}	-0.272^{***}
			(0.105)	(0.103)
Mom				0.307^{***}
				(0.052)

Note: *p<0.1; **p<0.05; ***p<0.01

Table XXV. Time Series Regression Analysis Strategy 5 S&P 500

The table reports coefficients obtained from the four following time-series regressions on returns of the portfolio built with strategy 5.
$(1) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + \epsilon_t$
$(2) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + \epsilon_t$
$(3) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \epsilon_t$
$(4) R_i - RF = \alpha_i + \beta_i * (Mkt - RF) + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + p_i * MOM_t + \epsilon_t$
The portfolios are created by applying strategy 5 on the S&P 500 index. Strategy 5 is a long strategy where the stocks of the ten companies with the highest average Sentiment-Score in the previous week will be bought. The portfolios are rebalanced weekly. Each regression is estimated with daily data over the observation period from 5 March 2018 to 30 April 2019. MktRf is excess daily market return, SMB is the return of a portfolio long small stocks and short large stocks, HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks, RMW is the return of a portfolio long high operating profitability stocks and short low operating profitability stocks, CMA is the return of a portfolio long high investment stocks and short low investment stocks and Mom denotes the momentum factor proposed by Carhart (1997). Standard errors (reported in parentheses) are adjusted for serial correlation using the Newey-West correction.

	Dependent variable:			
	Strategy Return - RF			
	(1)	(2)	(3)	(4)
Alpha	0.0003	0.0001	0.0001	0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
MktRF	1.163***	1.116***	1.120***	1.128***
	(0.046)	(0.050)	(0.049)	(0.046)
SMB		−0.361***	−0.365***	−0.273***
		(0.062)	(0.065)	(0.061)
HML		−0.251***	−0.271***	−0.098
		(0.070)	(0.083)	(0.097)
RMW			−0.044	0.044
			(0.091)	(0.088)
CMA			0.055	0.072
			(0.161)	(0.155)
Mom				0.292***
				(0.082)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table XXVI. Excerpt of list of executed trades of strategy 5 on the S&P 500 index

The table provides an excerpt of 25 of the 421 executed trades of strategy 5 on the S&P 500. The ISIN identifies the company affected by the trade. Opensignal indicates if a long position (1) or a short position (-1). Openingprice shows the price at which a trade was entered and closingprice the price at which a position was closed. Holding period shows the number of days a trade was open. The whole list of this and all the other strategies can be output with the R code belonging to this work.

isin	opendate	opensignal	openprice	closedate	closesignal	closeprice	holding_period	trade_return
CH0001319265	11.06.18	1	6203.07	25.06.18	0	5192.8	14	-0.1629
CH0001319265	13.08.18	1	6162.66	20.08.18	0	6182.86	7	0.0033
CH0001319265	27.08.18	1	6364.71	24.09.18	0	5637.32	28	-0.1143
CH0001319265	10.12.18	1	5455.47	17.12.18	0	5253.41	7	-0.0370
CH0002088976	14.01.19	1	242.57	26.03.18	0	123.44	-294	-0.4911
CH0002168083	03.12.18	1	151.38	21.01.19	0	187.47	49	0.2384
CH0002168083	28.01.19	1	184.83	04.02.19	0	166.51	7	-0.0991
CH0002168083	15.04.19	1	216.37	04.22.19	0	218.07	7	0.0079
CH0002168083	29.04.19	1	221.67	20.05.19	0	221.67	21	0.0000
CH0002497458	03.12.18	1	2553.17	26.03.18	0	2444.01	14	-0.04282
CH0002497458	09.04.18	1	2520.75	30.04.18	0	2576.17	21	0.0220
CH0002497458	21.05.18	1	2727.52	28.05.18	0	2742.45	7	0.0055
CH0002497458	23.07.18	1	2711.54	06.08.18	0	2778.69	14	0.0248
CH0002497458	22.10.18	1	2435.48	12.11.18	0	2455.73	21	0.0083
CH0002497458	24.12.18	1	2344.88	31.12.18	0	2355.54	7	0.0045
CH0002497458	02.11.19	1	2598.56	18.02.19	0	2657.18	7	0.02267
CH0003583256	04.06.18	1	23.8	23.07.18	0	153.95	49	5.4685
CH0008702190	03.09.18	1	59.92	18.03.19	0	58.7	196	-0.0204
CH0008742519	02.04.18	1	497.39	09.04.18	0	496.54	7	-0.0017
CH0008742519	16.04.18	1	500.5	07.05.18	0	507.44	21	0.0139
CH0008742519	04.06.18	1	494.11	11.06.18	0	493.12	7	-0.0020
CH0008742519	18.06.18	1	483.76	25.06.18	0	487.18	7	0.0071
CH0008742519	24.09.18	1	494.67	23.07.18	0	496.54	7	0.0038
CH0008742519	10.12.18	1	489.27	01.10.18	0	489.27	7	0.0000
CH0008742519	24.12.18	1	513.39	17.12.18	0	526.17	7	0.0249