Essays on financial market aspects of corporate lawsuits and investor sentiment in stock markets

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Abstract

This dissertation's first subject area considers the impact of legal proceedings on corporate valuation. The first paper of this subject area analyzes the shareholder wealth effects of corporate prosecution settlements in the U. S. from 2001 to 2014. The results show that the settlement of criminal prosecution leads to positive shareholder wealth effects due to the resolution of uncertainty. Stockholders generally view the announcement of plea agreements more positively than the announcement of deferred prosecution and non-prosecution agreements. Therefore, the argument that particularly large corporations are treated preferentially and suffer comparatively less when using pretrial diversions cannot be confirmed by the empirical results.

The second paper considers the reaction of banks' stocks, bonds, and credit default swaps to the announcements of monetary penalties. From 2005 to 2015, the 25 largest global financial institutions paid combined more than $285 billion in legal penalties. A reduction in default risk and lower financing costs, as well an increase in the stock market valuation is observed, suggesting that banks benefit from settling lawsuits. Again, the positive reaction is likely driven by the resolution of uncertainty. While the sued bank's systemic risk increases in the size of the relative monetary penalty, also positive spillover effects to other banks facing pending lawsuits with the same plaintiff are observed, demonstrating the systemic effect of law enforcement against banks. Furthermore, banks appear to correctly anticipate penalties, as they are cash flow-effective but not income-effective in the year they are announced.

In the second subject area of this dissertation, the impact of self-disclosed sentiment on the stock market is investigated using the two major social media platforms Seeking Alpha (SA) and StockTwits (ST). It is found that negative self-disclosed sentiment on SA produces economically significant negative returns on the next day. In contrast, self-disclosed disagreement and positive self-disclosed sentiment on ST induce significant trading volume the next day. Both effects are predominantly driven by small stocks. The results indicate that self-disclosed sentiment is a powerful means of measurement and that the quality oriented SA is connected to stock returns while the quantity oriented ST is connected to trading activity.

I thank my wife Anne and my
supervisor Dirk Schiereck for their support.

Für Mama und Papa.

Contents

Chapter 1
Synopsis

This thesis consists of three chapters which are identical to three papers that are published or intended for publication in scientific journals. The chapters can be assigned to two main subject areas. The first subject area is the influence of the settlement of law enforcement activities on corporations in general and banks in particular. The second subject area is the role of investor sentiment in stock markets. Both subject areas address the information evaluation and processing in financial markets. The first two papers focus on the resolution of information uncertainty, the third concentrates on ongoing information valuation over time.

To ensure the functioning of the economy, to remedy market failures, and to generally uphold the rule of law, economic activity is regulated. Setting the legal framework is, however, only half of the story. The law also has to be enforced and corporations regularly face legal proceedings and large financial penalties. In the recent past this has been particularly true for financial institutions due to their misconduct in connection with the global financial crisis. Because of its central importance for the economy the financial sector is, however, in general particularly affected by law enforcement and regulation. From 2005 to 2015, the 25 largest global financial institutions combined paid more than 285 billion US dollars in penalties, which corresponds to approximately 20% of their 2004 year-end market value. Prominent settlement cases include, among others, Bank of America in August 2014 for almost $17 billion with the U. S. Department of Justice (DOJ) for financial fraud leading up to and during the global financial crisis, BNP Paribas in June 2014 for approximately $9 billion with multiple US authorities for violations of US sanctions, and UBS's $19 billion agreement with the New York Justice Department for the misrepresentation of securities in August 2008. But also outside the financial industry large legal settlements can be regularly observed. A particularity of the law system in the United States is that corporations are frequently also criminally prosecuted. One of the most prominent corporate criminal prosecutions in recent years is connected to the Deepwater Horizon oil spill of 2010, which caused one of the largest environmental catastrophes in U. S. history. BP as the ultimate platform operator subsequently settled criminal and civil claims and paid penalties of 4 billion US dollars in 2012 and an additional 18.5 billion US dollars in 2015. A more recent example of federal corporate prosecution is the emissions scandal of Volkswagen. Civil charges have been resolved in June 2016 with a payment of 15.3 billion US dollars and criminal charges in April 2017 with the payment of a 2.8 billion US dollars fine. These recent examples of large legal settlements exemplify that the topic of large legal settlements against non-financial corporations, as well as against large, systemically important banks, is of significant research and policy relevance.

Chapters 2 and 3 belong to the first subject area of this dissertation. Chapter 2 has been published in the Journal of Business Research in 2017 with the title “Settlement agreement types of federal corporate prosecution in the U. S. and their impact on shareholder wealth” (Flore, Kolaric, and Schiereck, 2017). It investigates the nature and implications of criminal prosecutions of corporations in the United States and is the first study to consider the wealth implications of their settlement for shareholders. Chapter 3 has been published in the Journal of Corporate Finance in 2021 with the title “Forgive me all my sins: How penalties imposed on banks travel through markets” (Flore, Degryse, Kolaric, and Schiereck, 2021). This investigation is different from the first one in the respect that it focuses on banks. At the same time it extends the scope of investigation and makes contributions to the existing literature in multiple ways. First, it includes all known legal enforcement actions against the sample banks in the United States as well as in Europe that lead to a monetary penalty and therefore is not restricted to a particular enforcement type. Second, this study goes beyond the stock market and also considers the debt market as well as the default risk of a bank by analyzing credit default swap spreads. Third, it investigates how financial penalties disseminate from the equity to debt and credit-default swap markets, thereby showing the interrelationship between these markets. Fourth, it investigates the spillover effects of settlements to comparable large financial institutions and whether the size of the settlements impacts the sued banks’ contribution to systemic risk. Fifth and finally, it investigates the effect of penalties on bank’s financial statements and subsequent lending behaviour. This allows for conclusions on how penalties affect banks’ liquidity, profitability, but also lending activities towards the real sector.

In Chapter 2 the shareholder wealth effects of corporate prosecution settlements in the U. S. are analyzed using a comprehensive sample of 100 Prosecutions Agreements (PAs), 64 Deferred Prosecution Agreements (DPAs), and 63 Non-Prosecution Agreements (NPAs) between January 2001 and December 2014. DPAs and NPAs, also named “pre-trial diversions”, first emerged in the 1990s as a means to resolve corporate prosecutions (Alexander and Cohen, 2015) and in contrast to PAs these settlements do not involve the admission of guilt or the defendant’s conviction. Charges against the company will be dropped or not brought to trial if the firm complies to the agreement’s terms.

Overall, significant and positive shareholder wealth effects to the announcement of the settlement of criminal prosecutions are documented, indicating that investors generally view settlements as positive information. The use of pretrial diversions thereby does not appear to be more beneficial for firms than the use of PAs. On the contrary, the announcement of settlements through DPAs or NPAs leads to significantly lower share price reactions than the announcement of settlements through PAs, suggesting that shareholders favor PAs over pretrial diversions. Therefore, the argument that particularly large corporations are treated preferentially and suffer comparatively less when using pretrial diversions cannot be confirmed by the empirical results, at least from a shareholder's perspective. The likelihood of a certain agreement type is strongly dependent on the crime committed. Corporate governance seems to be of importance as poorer board-related governance structures are associated with an increased likelihood of a criminal conviction through a PA.

In Chapter 3 the impact of the settlement of law enforcement activities on banks is analyzed and for this purpose data has been hand-collected on more than 400 legal settlements that involved at least one of the 25 largest global financial institutions between 2005 and 2015. After controlling for other, stock price relevant events surrounding the settlement announcement to ensure that the measured effect is due to the settlement announcement itself, a final sample of 251 events is used for the analysis.

The results show significant positive valuation effects for the stock, bond, and CDS market, respectively. This suggests that the settlement of lawsuits is generally viewed as a positive event by capital market participants. At the time of the settlement negative information has already been priced in and the settlement itself reduces a bank's default risk as well as financing costs and increases its stock market valuation. It is further documented that larger settlements are associated with more pronounced stock market valuation effects, consistent with the resolution of greater degrees of uncertainty. Further substantiating this result, it is documented that banks with greater stock return volatility prior to the settlement, as an indicator for uncertainty, enjoy larger announcement effects in stock markets. The interactions between stock, bond, and CDS markets around resolution announcements are examined using a simultaneous regression framework. The results show that the settlement affects stock and CDS markets directly on the announcement day and that these markets transmit the effect to the bond market with a one day lag.

The resolution of legal enforcement actions has positive spillover effects towards comparable financial institutions with pending lawsuits from the same plaintiff. At the same time, weak evidence is found that a bank's contribution to systemic risk increases the larger the size of the relative monetary penalty. This evidence, albeit somewhat mixed, underscores the systemic relevance of law enforcement actions against banks, as pointed out by the European supervisory authorities (European Systemic Risk Board, 2015).

Additionally, it is evaluated whether a bank's annually paid monetary penalties have an impact on its cash flow, net income, tier 1 ratio, and lending. It is found that monetary penalties reduce annual cash flows nearly one-to-one in the announcement year, reflecting the cash flow-effectiveness of these settlements. In contrast, banks' net income is unaffected by the announced penalties, suggesting that monetary penalties are not income-effective in the year they are announced. Yet, as they are cash flow-effective, this provides tentative evidence that banks appropriately account for impending penalties prior to the fiscal year of the resolution announcement. The settlement announcement effect should therefore be driven by the resolution of uncertainty.

The second subject area of this dissertation investigates the role of investor sentiment in stock markets. A few decades ago a common view of the stock market was that it is efficient and investors are rational (Fama, 1970). In this context, stock prices reflect all available information and follow a random walk without any foreseeable pattern. This standard finance model has considerable difficulties to explain some characteristics of the stock market, e. g., the regular occurrence of boom and bust cycles. Now it is clear that stock markets are not fully efficient and that irrational investor beliefs influence stock prices (Baker and Wurgler, 2007). Due to limits to arbitrage irrational stock valuations are not always immediately corrected by rational investors. Because the development of these irrational beliefs is hard to predict it is therefore hard and costly to bet against them. Further understanding the relevance of irrational investor sentiments for stock markets is a topic of considerable attention in current asset pricing research.

Investor sentiment reflects the actual beliefs of investors not taking into account whether these are based on a noise trader's irrational expectations or on a rational arbitrageur's Bayesian expectations. As pricing a stock means discounting a firm's future cash flows an investor has to make multiple assumptions about the future without a final resolution of uncertainty. Investors are considered to be rational if their assumptions are based on fundamental values and Bayesian probabilities. In contrast, irrational investors, or noise traders, form their (biased) beliefs mainly based on their emotion. The fundamental value of a firm is that value at which a rational investor would arrive if he possessed all available information. A stock's price can deviate from this fundamental value due to two reasons: information uncertainty and asymmetry as well as noise trading. In the case of informational asymmetry, not all rational investors have access to the same information. If the information advantage is large and closely held, it will take time to include this information in stock prices. In the case of noise trading, a deviation from the fundamental value arises due to the beliefs of irrational investors.

Investor sentiment can be measured by various means, by using market-based proxies like the number of initial public offerings or stock repurchases, by using surveys, or by analyzing news and social media. The digitalization of traditional newspaper outlets has played a key role in the exponential increase in the speed and quantity of information impounded into the prices of financial assets. Online news media, combined with the rising popularity of social media platforms, has enabled investors to easily access financial information which affects their investment decisions. Large social media platforms differentiate themselves from more traditional news media, like newspapers for example, in that the sentiment measurement becomes more direct on the level of individual investors. This development presents novel possibilities for researchers to investigate the effect of investor sentiment on stock prices.

Chapter 4 belongs to the second subject area of this dissertation. It is a working paper with the title “Social media sentiment and the stock market: Quality vs. quantity” and intended for publication in a scientific journal (Flore, Leung, and Ton, 2021). It investigates the influence of sentiment derived from social media on the stock market. More specifically, this study’s main contributions are as follows. First, it is the first study to jointly examine the effect of different sentiment sources. Second, it is the first investigation in the usefulness of self-disclosed sentiment for stock return prediction since Tumarkin and Whitelaw, 2001 who do not find any significant effect on future stock returns. Third, it studies the short-term sentiment effects of social media on stock returns for which there has not been shown comprehensive evidence of a sentiment effect yet.

To achieve the aforementioned contributions this study leverages the unique features of data from two social media platforms, Seeking Alpha (SA), which contains articles classified into buy/sell categories by the author, and StockTwits (ST), which contains shorter messages tagged with author-disclosed sentiment. These direct measures of sentiment improve upon media tone measures used in prior literature by reducing the likelihood of misclassification due to the use of textual analysis techniques. The study jointly examines the effect of sentiment on stock price returns and trading volume from 81,768 SA articles covering financial analysis and stock research, 31,281,048 ST social network messages (tweets) focused on the discussion of stocks, as well as 11,435,975 RavenPack (RP) news events derived from news media sources, like, e. g., Dow Jones Financial Wires, Wall Street Journal, and company press releases. Articles on SA are either qualified as “long” or “short” by the authors themselves and on ST users can mark their message as “bearish” or “bullish” by clicking the respective button. In many ways, ST can be described as a version of Twitter for the stock market. SA can be characterized as a more quality-oriented while ST as a more quantity-oriented social medium. Both social media platforms are highly likely to be accessible to different types of investors.

First, this study shows that negative self-disclosed sentiment from SA produces large negative returns the next day. ST and RP as well as media tone from SA also produce statistically significant return predictions which are, however, economically small and vastly under-perform the predictive power of SA self-disclosed sentiment. There are three possible explanations why this sentiment effect arises. First, in the case that prices are moved by rational traders, SA contains new price-relevant information before it is factored into the stock price, while ST and RP do not. Second, in the case that prices are moved by noise traders, SA, ST, and RP may be used by separate groups of investors and only the irrational sentiment of SA users is representative of a group of investors with enough market power that actually moves stock prices. Third, the out-performance of SA self-disclosed sentiment may also arise because the means of measurement, i. e., self-disclosure, works considerably better for SA than it does for ST. This explanation is possible assuming both, rational traders or noise traders. Although it is hard to differentiate between the possible reasons, the persistence of the sentiment effect, i. e., the lack of a return reversal, indicates price-relevant informational content in SA self-disclosed sentiment. Furthermore, it seems that self-disclosed sentiment from ST in fact measures investor sentiment, as shown by the second main result.

Second, it is found that self-disclosed disagreement and positive self-disclosed sentiment from ST induce trading volume the next day, while SA and RP, as well as ST sentiment tone do not. This suggests that self-disclosure represents relevant investor sentiments on ST. These sentiments are, however, related to trading activity and not to stock returns. A reason for this could be that this activity is generated by noise traders who trade among themselves or with rational traders. The lack of a significant stock movement then indicates that no rational trading takes place, i. e., no new information are processed. It seems that for trading activity the quantity oriented nature of ST delivers a much better indication and that the quality oriented nature of SA delivers a much better indication of stock returns.

Third, it is demonstrated that the sentiment effect on returns as well as the effect on trading volume are predominantly driven by small stocks where the activity of institutional trading is limited due to liquidity concerns. The average daily difference of returns from a positive self-disclosed SA sentiment portfolio over a negative sentiment increases by roughly 120% for firms below the first size tercile. One reason for the fact that the sentiment effect is so concentrated among small stocks maybe that the distribution of information about small stocks is more asymmetric and trading rather illiquid. In an asymmetric informational and illiquid market context, investor sentiment plays a more important role. For rational investors this means that price-relevant information may diffuse more slowly thereby causing a lagged reaction. For an irrational investor the fewer information about a firm is available the more is left to the investor's imagination which then makes her more sensitive to sentiment. Another explanation for the size dependence of the sentiment effect is that small stocks have higher individual investor ownerships. If the used sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks better.

The rest of this dissertation is structured as follows. Chapters 2, 3, and 4 each present the respective papers. Chapter 5 then concludes this dissertation.

Chapter 2
Settlement agreement types of federal corporate prosecution in the U. S. and their impact on shareholder wealth

Abstract

This paper analyzes the shareholder wealth effects of corporate prosecution settlements in the U. S. from 2001 to 2014. We focus on the relative monetary size of the settlement and on deferred prosecution and non-prosecution agreements in contrast to traditional plea agreements. The results show that the settlement of criminal prosecution leads to positive shareholder wealth effects, which may be due to the resolution of any remaining uncertainty with respect to the total settlement amount and lower than expected settlement costs. Stockholders generally view the announcement of plea agreements more positively than the announcement of deferred prosecution and non-prosecution agreements. The likelihood of a certain agreement type is strongly dependent on the crime committed. Moreover, larger firms with better board-related governance structures that have not been criminally prosecuted prior to the settlement are more likely to avoid a criminal conviction.[1]

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Chapter 3

Forgive me all my sins: How penalties imposed on banks travel through markets

Abstract

From 2005 to 2015, the 25 largest global financial institutions paid combined more than $285 billion in legal penalties. We examine the reaction of banks' stocks, bonds, and credit default swaps to the announcements of monetary penalties. We observe a reduced default risk and lower financing costs, as well an increase in the stock market valuation, suggesting that banks benefit from settling lawsuits. The positive reaction is likely driven by the resolution of uncertainty surrounding these proceedings. While the sued bank's systemic risk increases in the size of the relative monetary penalty, we also document positive spillover effects to other banks facing pending lawsuits with the same plaintiff, demonstrating the systemic effect of law enforcement against banks. Furthermore, banks appear to correctly anticipate penalties, as they are cash flow-effective but not income-effective in the year they are announced.[1]

This chapter has been published as:

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Chapter 4

Social media sentiment and the stock market: Quality vs. quantity

Abstract

We compare the impact of self-disclosed sentiment on the stock market from the two major social media platforms SeekingAlpha (SA) and StockTwits (ST) against a sentiment tone measure based on the percentage of negative words in a post. We find that negative self-disclosed sentiment on SA produces economically significant negative returns on the next day. In contrast, self-disclosed disagreement and positive self-disclosed sentiment on ST induce significant trading volume the next day. Both effects are predominantly driven by small stocks. The results indicate that self-disclosed sentiment is a powerful means of measurement and that the quality oriented SA is connected to stock returns while the quantity oriented ST is connected to trading activity.

This chapter is a working paper and has not been published yet.

Christian Flore, Henry Leung, and Thai Ton (2021). "Social Media Sentiment and the Stock Market: Quality vs. Quantity." Working Paper

4.1 Introduction

The digitalization of traditional newspaper outlets has played a key role in the increase in the speed and quantity of information impounded into the prices of financial assets. Online news media, combined with the rising popularity of social media platforms, have enabled investors to access financial information more easily. This affects their investment decisions and is thereby connected to stock price returns and trading volumes. This study leverages the unique features of data from two social media platforms, Seeking Alpha (SA), which contains longer articles classified into buy/sell categories by the author, and StockTwits (ST), which contains shorter messages that are also often tagged with author-disclosed sentiment. These direct disclosures of sentiment are particularly interesting as they reveal the actual investor sentiment. We compare this direct source of sentiment against sentiment tone, which is computed using the percentage of negative words that match the Loughran and McDonald, 2011 dictionary.

We jointly examine the effect of investor sentiment on stock price returns and trading volume from 81,768 SA articles covering financial analysis and stock research, 31,281,048 ST social network messages (tweets) focused on the discussion of stocks, as well as 11,435,975 RavenPack (RP) traditional news events derived from news media sources, like, e. g., Dow Jones Financial Wires, Wall Street Journal, and company press releases. We restrict our sample to the period from 2012 to 2017. During this time the three sources are well established and exhibit stable characteristics. For SA this period represents 92% of all available data and for ST it is 98%. SA articles have been on average approximately 820 words long in our dataset. Before publication, articles go through an editing process to ensure that certain standards of quality are met. Furthermore, the articles are either qualified as “long” or “short” by the authors themselves. ST is a social media platform that is different from SA in several ways. The main differences are that messages are restricted to a length of 140 characters and that there is no editorial process. The users can mark their message as “bearish” or “bullish” by clicking the respective button. In many ways, ST can be described as a version of Twitter for the stock market. Overall, SA is therefore a more quality-oriented while ST is a more quantity-oriented social medium. Both social media platforms are highly likely to be accessible to different types of investors.

The pricing of a stock implies that an investor needs to make multiple assumptions about the future outlook of the firm. We consider investors to be rational if their assumptions are based on fundamental values and Bayesian probabilities. In contrast, irrational investors, or noise traders, form their beliefs mainly based on their emotion. We define the fundamental value of a firm as that value at which a rational investor would arrive at if s/he possessed all available information. A stock's valuation can deviate from this fundamental value due to two reasons: information asymmetry and noise trading. In the case of information asymmetry, not all rational investors have access to the same set of information. If the market power of uninformed rational investors is large enough, they will move the price away from its fundamental value. In the case of noise trading, a deviation from the fundamental value arises due to the beliefs of irrational investors. The notion of misvaluation is supported by Hirshleifer and Jiang, 2010, who show that investor sentiment may lead to misvaluation of firms. As proxies for misvaluation they use equity and debt financing activities. A company for instance conducts initial public or seasoned equity offerings when managers think it is overvalued and it buys back stock when they think it is undervalued. This misvaluation affects multiple firms alike in a fashion similar to the size or valuation effect (Fama and French, 1992; Fama and French, 1993) and can likewise be expressed as a common risk factor. They show that firms that have been undervalued in the past, i. e., engaged in the respective financing activity, outperform overvalued firms quite significantly in the future. In this study, we find that the short-run buy and hold return differentials of portfolios based on the self-disclosed sentiment of ST messages suggest that the measure leads to stock misvaluation which is corrected later. However, return patterns of portfolios based on self-disclosed investor sentiment from SA suggest that this direct measure contains value-relevant information which contributes to the fundamental value of a firm.

The main contributions of this paper are threefold. First, to the best of our knowledge, this is the first study to jointly examine the effect of different sources of media sentiment on the stock market[1]. The disparate literature on different sentiment measures investigating different time horizons makes the relative comparison of the impact of social media sentiment sources difficult. Further, as these social media platforms are very diverse and probably also speak to different types of investors, it is particularly interesting to compare their respective effects on stock returns against a traditional sentiment measure of news media. The two social media platforms we examine in this study, SA and ST, are very different in nature. During our investigation period, 37 articles were published on SA per day on average, while for ST it is 14,283 Tweets per day on average. Both platforms may therefore attract different kinds of investors. Also, the different kinds of publications, e. g., SA articles are on average 820 words long and edited for quality while ST articles are on average 104 characters long and

[1]For literature on news media sentiment, see, e. g., Chan, 2003; Baker and Wurgler, 2007; Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Dougal, Engelberg, García, and Parsons, 2012; Gurun and Butler, 2012; Garcia, 2013; Jegadeesh and Wu, 2013; Huang, Jiang, Tu, and Zhou, 2015. For literature on internet social media sentiment, see, e. g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das and Chen, 2007; Chen, De, Hu, and Hwang, 2014; Da, Engelberg, and Gao, 2015; Renault, 2017; Cookson and Niessner, 2020.

not edited for quality, may allow for different sentiment measures to ensure comparability.

Second, to our knowledge, we are the first to investigate the usefulness of self-disclosed sentiment for stock return prediction. The effect of social finance media opinions have grown with the popularity of the internet as an opinion sharing medium by investors. During the nascent period of internet usage, Tumarkin and Whitelaw, 2001 do not find any significant effect of message board opinions on future stock returns in the 1999-2000 period. Since then, literature such as Antweiler and Frank, 2004 shows that investor sentiment tone imputed from online posts affects stock market activity. We show that self-disclosed investor sentiment contains price-relevant information beyond what investor sentiment tone may capture.

Third, we study the short-term sentiment effects of social media on stock returns. Although it has been shown that negative sentiment tone predicts negative stock returns over the medium-term (Chen, De, Hu, and Hwang, 2014) and intraday (Renault, 2017), researchers have so far failed to detect a significant sentiment effect over the short-term, i. e., the following days. We add to this literature by using a larger and more comprehensive dataset than previously used. Social media has evolved considerably over the past years. With respect to the data we use for this study approximately 96% of our downloaded media content was published after 2012. Therefore, a new attempt of showing a sentiment effect over the short-term is worthwhile.

We show that negative self-disclosed sentiment from SA produces large negative returns the next day. The average daily difference of returns from a positive sentiment portfolio over a negative sentiment portfolio is 0.40%. ST and RP as well as sentiment tone from SA also produce statistically significant return predictions which are, however, economically small and vastly under-perform the predictive power of SA self-disclosed sentiment. There are three possible explanations why this sentiment effect arises. First, in the case that prices are moved by rational traders, SA contains new price-relevant information before it is factored into the stock price, while ST and RP do not. Second, in the case that prices are moved by noise traders, SA, ST, and RP may be used by separate groups of investors and only the irrational sentiment of SA users is representative of a group of investors with enough market power that actually moves stock prices. Third, the out-performance of SA self-disclosed sentiment may also arise because the means of measurement, i. e., self-disclosure, works considerably better for SA than it does for ST. This explanation is possible assuming that users consist of both rational and noise traders. Although it is hard to differentiate between the possible reasons, the persistence of our sentiment effect, i. e., the lack of a return reversal, indicates price-relevant informational content in SA self-disclosed sentiment. For ST self-disclosed sentiment, on the other hand, a return reversal indicates noise or misvaluation characteristics. Furthermore, we find evidence that self-disclosed sentiment from ST in fact measures investor sentiment, as shown by our next set of results.

We find that self-disclosed disagreement and positive self-disclosed sentiment from ST induce trading volume the next day, while SA and RP, as well as ST sentiment tone do not. This suggests that self-disclosure represents relevant investor sentiments on ST. These sentiments are, however, related to trading activity and not to stock returns. A reason for this could be that this activity is generated by noise traders who trade among themselves or with rational traders. The lack of a significant stock movement then indicates that no rational trading takes place, i. e., no new information are processed. Results suggest that the quantity oriented nature of ST delivers a significantly better indication of the trading activity of stocks, and the quality oriented nature of SA delivers a much better indication of stock returns. We show that disagreement and positive sentiment on ST induce stock trading volume, which suggests that information from ST play an important role for noise traders. The argument is that if investors agree on ST they have to trade with different investors with whom they disagree. Consequently, disagreement between bullish noise traders on ST and rational traders are expected to drive trading volume.

We demonstrate that the sentiment effects on returns and trading volume are predominantly driven by small stocks. The average daily difference of returns from a positive self-disclosed SA sentiment portfolio over a negative sentiment increases to 0.88% for firms below the first size tercile. For small stocks a one standard deviation increase in self-disclosed ST disagreement increases the trading volume by nearly nine times the stock's market capitalization and a one standard deviation decrease in our self-disclosed ST sentiment measure (more positive sentiment) increases the trading volume by nearly ten times the stock's market capitalization. One reason for the fact that the sentiment effect is so concentrated among small stocks may be that the distribution of information about small stocks is more asymmetric. In an asymmetric informational context, investor sentiment plays a more important role. For rational investors this means that price-relevant information may diffuse more slowly thereby causing a lagged reaction. An irrational investor may become more uncertain around one's sentiment towards material firm specific information when fewer information about a firm is available. Another explanation for the size dependence of the sentiment effect is that small stocks have higher individual investor ownership. If our sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks more accurately.

The remainder of the paper is structured as follows. Section 2 discusses the literature. Section 3 describes the data used for the analysis. Section 4 contains a descriptive portfolio analysis and Section 5 contains a formal testing of sentiment returns. Section 6 examines sentiment's impact on stock liquidity and Section 7 concludes.

4.2 Literature

Three strands of literature align with our approaches in comparing the impact of investor media sentiment on the stock market. The first two approaches derive sentiment indirectly either from firm-specific proxies or from news media tone. The third approach derives sentiment more directly from investors on the internet and on social media.

Impact of investor sentiment indirectly derived from firm or market proxies

Various studies have examined the impact sentiment derived from firm-specific proxies on stock returns (e. g., Baker and Wurgler, 2006; Baker, Wurgler, and Yuan, 2012; Hirshleifer and Jiang, 2010; Da, Liu, and Schaumburg, 2014; Edelen, Ince, and Kadlec, 2016; Stambaugh and Yuan, 2017; Daniel, Hirshleifer, and Sun, 2020). Representative of this approach, two seminal papers can be named. Baker and Wurgler, 2006 show that when sentiment was high in one year for some stocks, these tend to earn low returns in the subsequent year. They consider as proxies for market wide sentiment the closed-end fund discount, stock exchange share turnover, the number and average first-day returns on initial public offerings, the equity share in new issues, and the dividend premium. Hirshleifer and Jiang, 2010 find that investor sentiment leads to misvaluation of firms. As proxies for misvaluation they use equity and debt financing activities. A company for instance conducts initial public or seasoned equity offerings when managers think it is overvalued and it buys back stock when they think it is undervalued. This misvaluation affects multiple firms alike in a fashion similar to the size or valuation effect (Fama and French, 1992; Fama and French, 1993) and can likewise be expressed as a common risk factor. They show that firms that have been undervalued in the past, i. e., engaged in the respective financing activity, outperform overvalued firms quite significantly in the future.

Impact of investor attention on stock returns

Another measure of investor behavior is investor attention. In the case of news or social media this measure is often investigated in addition to investor sentiment (e. g., Chan, 2003; Vega, 2006; Barber and Odean, 2008; Fang and Peress, 2009; Da, Engelberg, and Gao, 2011; Engelberg and Parsons, 2011; Solomon, 2012; Hillert, Jacobs, and Müller, 2014). Investor attention is, however, fundamentally different from sentiment in that it only considers the sheer number of times a stock it mentioned or searched. There exists no obvious relationship and Da, Engelberg, and Gao, 2011 find that there is actually very little correlation between both measures. It is shown that low investor attention can predict higher medium-term[2] stock returns. Fang and Peress, 2009 show that there exists a monthly return premium for stocks with little coverage in major U. S. newspapers in the preceding month. In contrast, other authors show that higher internet search volumes predict higher stock prices in the short-term. Da, Engelberg, and Gao, 2011 examine Google search volumes and find that an increase in in attention (i. e., search volume) predicts higher stock prices in the next two weeks and an eventual price reversal within the year. There is also evidence that the medium-term momentum effect in stock markets is stronger for firms with higher media coverage. Hillert, Jacobs, and Müller, 2014 collect news stories from four leading national as well as 41 local US newspapers. Media coverage is based on the number of firm-specific articles published in the six months of the portfolio formation period. They find that higher coverage stocks exhibit a higher medium-term momentum effect as well as a stronger long-term reversal.

The strands of literature related the closest to our study are regarding the second and third approach of investor sentiment measurement. That is, the indirect sentiment measurement from news media sources as well as the more direct measurement on the internet and social media. We will therefore review their literature in more detail in the following.

Impact of investor sentiment indirectly derived from news media

A strand of literature focuses on the effect of investor sentiment from news media on stock prices (e. g., Chan, 2003; Baker and Wurgler, 2007; Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Dougal, Engelberg, García, and Parsons, 2012; Gurun and Butler, 2012; Garcia, 2013; Jegadeesh and Wu, 2013; Huang, Jiang, Tu, and Zhou, 2015). Evidence reveals that investor sentiment derived from news media sources can predict stock returns over the short and medium-term whereat especially negative sentiment predicts negative stock returns. In a very early study, Chan, 2003 measures the sentiment of news stories mainly from the Dow Jones newswires by taking the stock returns on the same day as a proxy. News with returns in the top third are classified as good, and as bad in the bottom third. Stocks with so classified negative news continue to underperform in the subsequent months and up to twelve months for very negative news. Most of this return drift is on the downside among smaller, probably illiquid stocks. Chan, 2003 argues that more sophisticated investors may not be able to arbitrage away the pattern, since shorting is more expensive than buying.

[2]For the sake of structuring the literature findings we define short-term as the next trading days, medium-term as the next months, and long-term as everything beyond one year after sentiment measurement. We structure the empirical findings in this way because the observed effects are are entirely different in nature over the respective periods.

Investor sentiment also predicts short-term stock returns. One of the first papers to find evidence on a sentiment effect on stock returns is by Tetlock, 2007. They find that a pessimism factor mainly based on negative words in a Wall Street Journal column and according to the Harvard psychosocial dictionary can predict Dow Jones index returns. However, a negative reaction on the first day is followed by a reversion over the next four days. Tetlock, Saar-Tsechansky, and Macskassy, 2008 extend this analysis to address the impact of negative words in all Wall Street Journal and Dow Jones News Service stories about individual S&P 500 firms. Again the results show a negative, but small stock return on the next day responding to the information embedded in the percentage of negative words on the preceding day. Tetlock, Saar-Tsechansky, and Macskassy, 2008's overall conclusion is that the stock market is relatively efficient. The negative return is typically small as compared to the market's reaction on the day of the news publication. Garcia, 2013 show that the percentage of negative as well as percentage of positive words based on the Loughran and McDonald, 2011 dictionary in New York Times columns predict next day's Dow Jones index returns. They also find that this effect is particularly strong in recession times, arguing that economic recessions correspond with times of heightened sensitivity to news.

Short-term sentiment returns seem also to be larger for small firms. Tetlock, 2007 show that negative sentiment seems to have a longer-lasting and larger impact on small stocks over the next days. Their explanation is that small stocks have the highest individual investor ownership. If the pessimism factor measures the investor sentiment of individual investors, then it should predict the returns on small stocks better. In general, the more difficult and subjective the valuation of a firm is the more prone it is for misvaluations (Baker and Wurgler, 2007), which is particularly the case for small and young firms.

There is further evidence that negative sentiment predicts higher levels of trading volume over the short term (Tetlock, 2007). The absolute value of pessimism significantly predicts increases in volume on the next trading day. The straightforward interpretation is that high absolute values of pessimism are a proxy for disagreement between noise traders and rational traders, which leads to increases in trading volume on the next trading day.

Impact of sentiment measured on internet social media

A relatively smaller set of literature examines the effect of social media on the stock market (e. g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das and Chen, 2007; Chen, De, Hu, and Hwang, 2014; Da, Engelberg, and Gao, 2015; Renault, 2017; Cookson and Niessner, 2020). Early studies find no short-term stock return predictability of social media content. Tumarkin and Whitelaw, 2001 examine the sentiment on the RagingBull discussion forum over a period of one year. They use self-disclosed long short opinions to form a sentiment measure but find that this measure does not predict short-term stock returns over the following days. Antweiler and Frank, 2004 find that the effect of bullishness derived through machine learning classifications of Yahoo! Finance and Raging Bull messages on stock returns is insignificant for the 45 stocks part of the Dow Jones index. Although they did not find any effect of investor sentiment, they document that a positive shock to message board posting numbers, i. e., investor attention, predicts negative returns on the next day. This effect is statistically significant but economically small. Das and Chen, 2007 show that previous day's sentiment does not significantly predict stock returns on the next day. They downloaded messages from stock message boards of 24 "tech" companies over a short period of two months. Messages are classified by a machine learning algorithm including lexicon based counts of negative and positive words.

There is, however, more recent evidence that sentiment derived from internet social media influences medium-term, short-term, and intraday stock returns. With regard to the medium-term, Chen, De, Hu, and Hwang, 2014 observe that the fraction of negative words in SA articles and comments both negatively predict stock returns over the ensuing three months. Their study is the first to show that social media sentiment predicts stock returns. One interpretation of their findings is that views expressed on SA contain pieces of value-relevant information, which, as of the article publication date, are not fully factored into the price. Such an interpretation would point to the usefulness of social media outlets as a source of genuine, value-relevant advice. An alternative perspective is that SA views incite naive investor reaction. That is, SA views reflect false or spurious information yet still cause investors to trade in the direction of the underlying articles and comments and move prices accordingly. The observed lack of a return reversal are somewhat at odds with this interpretation. Moreover, whether followers of SA have enough capital by themselves to cause market prices to move in the manner that is documented in this study is unclear. Earnings-surprise predictability suggests that the opinions expressed on SA indeed provide value-relevant information (beyond that provided by financial analysts).

Although previous studies have shown no short-term effect of investor sentiment derived from social media on stock returns, Da, Engelberg, and Gao, 2015 show that market sentiment measured through web search volumes for negative words predict positive short-term stock returns. Market wide investor sentiment is measured through the internet search behavior of households and the authors find that the search for negative terms predicts high returns of a stock index on the following day.

Regarding the intraday effect of sentiment on stock prices there is evidence that negative sentiment predicts negative stock returns. Renault, 2017 uses a dictionary approach to measure general investor sentiment on ST and its effect on S&P 500 index ETF returns and find that the first half-hour change in investor sentiment predicts the last half-hour return.

Disagreement is a measure of investor sentiment where the homogeneity of sentiment is measured. High levels of sentiment, either positive or negative, thereby correspond to low levels of disagreement and vice versa. A traditional hypothesis is that disagreement induces trading. However, it has been shown that high levels of disagreement on Yahoo! Finance and Raging Bull predict higher levels of trading volume intraday but lower trading volume for the next day (Antweiler and Frank, 2004). Disagreement itself may be driven by investors relying on different information sets versus different interpretation of information, as shown by Cookson and Niessner, 2020.

Impact of self-disclosed investor sentiment

Literature is sparse on the impact of self-disclosed investor sentiment on the stock market, perhaps as a result of data limitation. Literature are shown to use derived measures of investor sentiment based on news media or internet social media. However, the tone of users' online media content is only a proxy of their sentiment (see, e. g., the percentage of negative words measure in Loughran and McDonald, 2011, which presumes that the share of negative words proxies a user's sentiment in a block of text). This may lead to inaccuracy in the measure which can be overcome by using self-disclosed sentiment where a user directly reveals her sentiment. The only study we know of that considers the impact of self-disclosed sentiment is one of the earliest studies on social media investor sentiment (Tumarkin and Whitelaw, 2001). The authors do not find any evidence on a return predictability of their self-disclosed sentiment measure. Another study is Renault, 2017, which uses the self-disclosed messages on ST as a training set for their machine learning algorithm which finally generates a media tone sentiment measure.

4.3 Data

We use data from three different media outlets, SA, ST, and RP. We therefor collected all articles from SA and all messages from ST since the start of their existence. From RP we use a readily available sentiment measure. Table 4.1 shows the collected data over the years.

SA is a social media platform where authors publish articles covering a broad range of asset classes. For the purpose of this study we focus on the section of stock ideas. Here authors publish articles presenting their take on the valuation of specific stocks. Between 2012 and 2017 these articles have been on average approximately 820 words long. According to SA, over 15 million unique users visit the platform in a month (SeekingAlpha.com, 2019). Before publication, articles go through an editing process to ensure that certain standards of quality are met. Furthermore, stock ideas are either qualified as “long” or “short” by the authors themselves. Table 4.1 shows all single ticker articles of stocks included in the CRSP database that are either classified as long or short from 2006 until 2017. Over the whole period 89,415 articles have been published of which 8.21% are classified as short and the remaining 91.79% as long. 5,362 different firms have been covered representing 40% of the total CRSP universe of 13,170 firms for the same period. The yearly number of articles increases sharply until 2012 and stays relatively stable from that year on. Before 2012 the share of short articles was very volatile and lower than it is in the following years, where it steadily stayed close to 10%.

ST is a social media platform that is different from SA in several ways. The main differences are that messages are restricted to a length of 140 words[3] and there is no editorial process. In many ways, ST can be described as version of Twitter for the stock market. The users reference their messages to specific stocks using so called “cash tags” analogous to the hash tag used by Twitter users. This cash tag allows us to reference messages to specific companies. Table 4.1 shows all downloaded messages from the ST database that contain a single ticker reference. Over the whole period 32,018,544 messages have been collected. Of these 30.09% are self-disclosed. The users can mark their message as “bearish” or “bullish” by clicking the respective button and while 24.88% mark their message as bullish, 5.21% mark them as bearish. A total of 7,683 firms are covered representing 58% of the total CRSP universe of 13,170 firms for the same period. The first messages are available in the year 2009. From that year on the number of messages increases steadily. From 2010 until 2014 the number of messages nearly doubles in most years and finally peaks at over 12 million in 2017. The share of self-disclosed messages starts to pick up in 2012 and is close to 30% for 2014 until 2017.

[3]The mean message length in our database from 2012 until 2017 is approximately 104 words.

Table 4.1: Description of Sentiment Databases.

This table shows descriptive statistics of the three databases over the years. The second column shows the number of different firms with stock returns in the CRSP database. For all further databases only those articles/tweets/stories are considered which can be attributed to precisely one firm with stock returns in CRSP. For SA, # art is the total number of short and long articles, # firms corresponds to the number of different firms covered, % short and % long are the percentage of articles categorized as short and long from all articles published, and % self-d. is the percentage of self-disclosed articles from all articles published. For ST, # tweets is the total number of tweets, # firms corresponds to the number of different firms covered, % bear and % bull are the percentage of tweets categorized as bearish and bullish from all tweets, and % self-d. is the percentage of self-disclosed tweets from all tweets. For RavenPack, # news events is the total number of RavenPack news events with a relevance score of 90 or higher, # firms corresponds to the number of different firms covered. % ESS>50, % ESS=50, and % ESS<50 are the percentages of news events with a Event Sentiment Score over, equal, and below 50, respectively.

	CRSP	Seeking Alpha					StockTwits					RavenPack				
	# firms	# articles	# firms	% short	% long	% self-d.	# tweets	# firms	% bear	% bull	% self-d.	# news events	# firms	% ESS>50 (positive)	% ESS=50 (neutral)	% ESS<50 (negative)
2006-17	13,170	89,415	5,362	8.21	91.79	100.00	32,018,544	7,683	5.21	24.88	30.09	17,606,924	8,591	47.78	25.22	26.99
2012-17	9,716	81,768	4,910	8.67	91.33	100.00	31,281,048	7,269	5.33	25.46	30.80	11,435,975	6,237	47.31	25.65	27.04
2006	7,445	151	135	0.66	99.34	100.00						570,172	5,217	49.46	28.47	22.08
2007	7,707	599	410	5.68	94.32	100.00						978,847	5,361	49.45	21.78	28.77
2008	7,421	978	557	5.83	94.17	100.00						1,061,858	5,112	47.11	23.12	29.78
2009	7,173	1,055	616	1.61	98.39	100.00	28,288	1,968	0.00	0.00	0.00	1,101,050	4,774	45.85	25.21	28.94
2010	7,135	1,192	707	0.50	99.50	100.00	205,454	3,850	0.03	0.11	0.14	1,062,113	4,655	50.00	25.15	24.85
2011	7,151	3,672	1,115	3.76	96.24	100.00	503,754	4,709	0.01	0.05	0.07	1,396,909	4,553	50.18	24.50	25.32
2012	7,168	11,373	1,707	9.14	90.86	100.00	994,730	5,051	0.69	2.59	3.28	1,832,045	4,466	48.62	25.66	25.72
2013	7,192	12,944	2,501	8.26	91.74	100.00	2,316,755	5,623	3.17	12.06	15.23	1,862,088	4,467	48.92	24.98	26.10
2014	7,442	15,756	2,646	7.18	92.82	100.00	4,032,574	5,890	4.79	21.75	26.54	1,810,219	4,580	47.72	25.76	26.52
2015	7,642	15,895	2,826	8.04	91.96	100.00	4,910,575	5,806	5.64	23.82	29.46	1,981,892	4,729	47.45	25.82	26.73
2016	7,608	13,187	2,506	11.64	88.36	100.00	6,656,099	5,635	5.58	27.44	33.03	1,998,755	4,631	45.82	25.51	28.67
2017	7,555	12,613	2,460	8.21	91.79	100.00	12,370,315	5,499	6.03	30.61	36.64	1,950,976	4,570	45.52	26.15	28.32

We also employ the Event Sentiment Score (ESS)[4] of traditional news media from RavenPack News Analytics (RP). RavenPack is a commercial provider of big data analytics. It collects news stories mainly from traditional media outlets like the Dow Jones Financial Wires, the Wall Street Journal, Barron's and MarketWatch, company press releases, regulatory, corporate and news services, business publishers, national and local news, blog sites, the government, and regulatory updates. Each news event is evaluated and sentiment scores are calculated determining how positive or negative an event should be. The ESS score ranges from 0-100, where 50 indicates neutral sentiment, values above 50 indicate positive sentiment, and below 50 negative sentiment. For the purpose of constructing the ESS, news stories are systematically compared with categories classified by financial experts. The sentiment data provided by RP is available on a story level. To match each news story with the relevant firm entity, RP assigns relevance scores between 0 and 100 to measure how strongly the news stories and the firm entities are related. The relevance score considers for example key words, mentions, firm role in the specific event, or the text positioning (headline vs. body). A headline story about a firm, results in a relevance score of at least 90 for the respective firm. According to RP, sentiment scores are especially applicable in settings with relevance scores greater than 90. We therefore follow their recommendation and only include firm-level news events with relevance scores greater than 90.[5] As can be seen in Table 4.1, over the total sample period from 2006-17 we have sentiment scores for a total of 17,606,924 news events, covering a total of 8,591 firms or 65% of the CRSP universe. Over this period around 25% of news events are classified as neutral, 27% as negative, and 48% as positive. With regard to the timely development, since 2012 the number of observations stayed relatively steadily close to 2 mio. per year and also the distribution of sentiment stayed relatively stable.

For our subsequent analysis we restrict our sample to the period from 2012 to 2017. During this time our three sources are well established and exhibit stable characteristics. Especially SA and ST have not been well established before 2012. Until then both platforms grew very rapidly. That is why for SA we only lose 8% of the total dataset and for ST only 2% by restricting our dataset to this common period.

We obtain our daily trading data (stock returns, market capitalization and trading volume) from the Center for Research in Security Prices (CRSP). We include all stocks from the New York Stock Exchange (NYSE), the American Stock Exchange (NYSE MKT formerly AMEX), and the National Association of Securities Dealers Automated Quotations

[4]As a robustness check we also use another sentiment score provided by RavenPack, the composite sentiment score (CSS). The results remain the same.

[5]Information are drawn from the RavenPack News Analytics 4.0 User Guide (RavenPack News Analytics, 2016) and Service Overview. For further details please contact RavenPack News Analytics.

(NASDAQ). Since our study does not limit to the universe of large stocks, which are mainly listed on NYSE, we consider all three major stock exchanges for our further analysis. To understand the comprehensive news sentiment impact on cross-sectional returns of all stocks, we also include smaller stocks and do not filter our data for example due to liquidity concerns (e. g., by price thresholds or size). We draw our fundamental data from the merged Compustat/CRSP data base. The descriptive statistics for the variables used in this paper are shown in Table 4.2.

Table 4.2: Variable Description.

This table shows selected statistical properties of the variables employed. The total sample consists of all firms in CRSP with at least one stock return in the time frame form 2012 until 2017. Panel A shows the variables with a daily resolution: Return is the total return calculated with daily closing prices and corrected for dividend payments, Abnormal return is calculated with the Fama French Five Factor Model over a time period of 252 trading days starting on the preceding day. The Buy and hold abnormal return is the cumulated abnormal return over the preceding 252 trading days and the Idiosyncratic volatility is the abnormal return's standard deviation over the preceding 252 trading days. Trading volume/market cap is the ratio of a share's daily trading volume and its market capitalization. Bid-ask spread is the difference of the highest bid price and the lowest ask price relative to the ask price at the daily closing time. SA # articles is equal to the number of SA articles for a specific firm on a specific day, and equal to zero if no articles exist. SA % short articles is the percentage of articles classified as "short" from all articles published for a specific firm on a specific day and missing if no articles exist. SA % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no articles exist. ST # tweets is equal to the number of ST tweets for a specific firm on a specific day, and equal to zero if no tweets exist. ST % self-disclosed tweets is the percentage of tweets classified as either "bullish" or "bearish" from all tweets for a specific firm on a specific day and missing if no tweets exist. ST % bear tweets is the percentage of tweets classified as "bearish" from all self-disclosed tweets for a specific firm on a specific day and missing if no self-disclosed articles exist. ST % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no tweets exist. The classification of negative words in SA articles and ST tweets is based on those words that match the Loughran and McDonald, 2011 dictionary. RP mean ESS (inverted) corresponds to the mean inverted Event Sentiment Score of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. Panel B shows the variables with a yearly resolution. All variables relate to their respective values at the previous financial year end. Market value is a firm's market value in thousand US-$, Book-to-market is the ratio of a firm's book and market value, and Return on assets is a firm's yearly net income divided by its total assets. The variables Return, Abnormal return, Trading volume/market cap, Bid ask spread, Buy and hold abnormal return, Book-to-market, and Return on assets are winsorized at the 0.5 and 99.5% level.

	Observ.	Mean	Std. error	Max.	90. pctle	Median	10. pctle	Min
Panel A: Firm-day								
Return (%)	10,455,119	0.03	2.34	11.07	2.23	0.00	−2.24	−9.60
Abnormal return (%)	10,439,512	−0.02	2.19	10.86	1.89	−0.02	−2.01	−9.50
Buy and hold abn. return (%)	10,455,119	−4.66	26.32	118.84	20.17	−3.01	−35.24	−84.06
Idiosyncratic volatility (%)	10,440,074	2.06	2.11	132.06	4.16	1.51	0.50	0.00
Trading vol./market cap (%)	10,088,953	119.74	424.08	4,411.77	205.83	22.14	3.21	0.00
Bid-ask spread (%)	10,455,041	0.56	1.25	9.46	1.43	0.13	0.02	0.01
SA # articles	10,455,119	0.01	0.10	16.00	0.00	0.00	0.00	0.00
SA % short articles (%)	72,132	8.24	26.80	100.00	0.00	0.00	0.00	0.00
SA % negative words (%)	72,132	2.19	1.31	15.05	3.85	1.99	0.75	0.00
ST # tweets	10,455,119	2.99	54.78	36,376.00	3.00	0.00	0.00	0.00
ST % self-disclosed tweets (%)	2,686,183	14.68	26.98	100.00	50.00	0.00	0.00	0.00
ST % bear of self-d. tweets (%)	867,621	17.43	32.38	100.00	100.00	0.00	0.00	0.00
ST % negative words (%)	2,685,404	1.14	2.91	100.00	3.61	0.00	0.00	0.00
RP mean ESS (inverted)	2,286,334	47.40	10.37	100.00	60.00	49.29	36.00	0.00
Panel B: Firm-year								
Market value	41,363	3,806,992	17,441,746	643,120,113	6,596,578	367,202	21,351	120
Book-to-market	27,935	1.57	5.78	61.64	1.85	0.59	0.12	−1.57
Return on assets (%)	28,120	−3.96	25.79	47.85	10.89	1.72	−24.92	−175.81

4.4 Descriptive results

4.4.1 Portfolio returns of different sentiment sources and measures

As a first descriptive check on the influence of investor sentiment on stock returns we consider the returns of stock portfolios formed on the basis of previous investor sentiment. It is impossible to investigate the contemporaneous influence of sentiment on stock returns due to the inherent endogeneity between returns and sentiment, i. e., stock returns affect investor sentiment as well as the other way around. We address this problem of reversed causality by looking at the predictive power of investor sentiment measures on future stock returns. We consider the short-term effects of investor sentiment using daily returns.[6] Table 4.3 shows mean daily returns of portfolios formed on the basis of sentiment measures on day 0. The Table shows returns from three days before (-3d) until twelve days after sentiment measurement (+12d). Based on our five sentiment measures stocks are assigned to three different portfolios: negative, neutral, and positive. To ensure that all observations have equal weights, each stock is bought with the same amount and the portfolios are value-weighted. Each panel of Table 4.3 shows portfolio returns based on different sentiment measures. Our main point of interest can be seen in row four of each panel. It is the return difference of the positive and the negative portfolio. Row five then shows the cumulative portfolio returns which sum the logarithmic return differences from +1d until the respective column's day. Panels A and C show portfolio returns based on a self-disclosed sentiment measure from SA and ST. If all articles (tweets) on SA (ST) on a given day are self-disclosed as short (bearish), the respective stock is assigned to the negative portfolio. If all articles (tweets) are labelled as long (bullish), the stock is assigned to the positive portfolio. If articles (tweets) of a stock are both labelled as short (bearish) and long (bullish) on a given day the stock is assigned to the neutral portfolio. We choose these cut offs because it is the most extreme formulation that selects only the stocks with the most positive and most negative sentiments for the respective portfolios. Panels B and D show portfolio returns based on a media tone sentiment measure which lists the percentage of negative words from the sum of negative and positive words. Stocks are assigned to the negative portfolio if the percentage lies above the 80th percentile of that day, as positive if it lies below the

[6] In a short term context it is particularly important to account for trading times. We use closing prices from NYSE, AMEX, and NASDAQ which close at 4pm. Given that we have exact time stamps of our social media content we assign all content published after 4pm, and on non-trading days to the following trading day.

20th percentile, and as neutral for everything in between.[7] Panel E uses RavenPack's Event Sentiment Score as the sentiment variable, applying the same differentiating logic as for the media tone portfolios described before with 20% and 80% as the respective cutoffs.

Table 4.3: Mean Daily Portfolio Returns.

This table shows the mean daily percentage returns of different portfolios on days -3d to +12d. The portfolios are formed based on the sentiment on day 0, which is classified into the three categories, negative, neutral, and positive. To ensure that all observations have equal weights, each stock is bought with the same amount and the portfolios are value-weighted. For each Panel the rows one to three show the mean daily portfolio returns. Row four shows the mean daily return differential between the positive and the negative portfolio and row five shows this mean return differential for a one day holding period (+1d until +1d) to a holding period of 12 days (+1d until +12d). The different panels relate to different sentiment sources for the classification of negative, neutral, and positive sentiment. Panel A shows the portfolio returns based on SA for the percentage of bear articles from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day, as positive if there are 0% short articles, and as neutral for all percentages in-between. Panel B uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel C shows the portfolio returns based on ST for the percentage of bear tweets from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day, as positive if there are 0% bear tweets, and as neutral for all percentages in-between. Panel D uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel E shows mean portfolio returns bases on the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day, as positive if it is in the bottom 20%, and else neutral.

	-3d	-2d	-1d	+0d	+1d	+2d	+3d	+4d	+5d	+6d	+7d	+8d	+9d	+10d	+11d	+12d
Panel A: Seeking Alpha percent short articles (0%=positive, 100%=negative)																
Negative	−0.06	−0.05	−0.09	−0.80	−0.28	−0.07	0.03	−0.03	−0.06	−0.03	−0.08	−0.06	0.00	−0.03	0.05	0.05
Neutral	−0.06	−0.08	−0.15	−0.39	0.01	0.00	−0.02	−0.01	−0.01	0.04	0.04	−0.01	0.09	0.18	−0.03	−0.02
Positive	0.08	0.11	0.13	0.26	0.12	0.08	0.03	0.05	0.04	0.05	0.04	0.04	0.03	0.04	0.03	0.04
Pos - neg	0.15	0.16	0.23	1.05	0.40	0.14	0.00	0.08	0.09	0.08	0.12	0.10	0.03	0.07	−0.03	−0.01
Pos - neg (cum)					0.40	0.54	0.55	0.63	0.72	0.80	0.92	1.02	1.06	1.13	1.10	1.09
Panel B: Seeking Alpha percent negative words (bottom 20%=positive, top 20%=negative)																
Negative	−0.15	−0.26	−0.31	−0.18	0.00	0.03	0.02	0.06	0.03	0.06	−0.04	0.02	0.06	0.01	0.05	0.02
Neutral	0.11	0.21	0.23	0.26	0.11	0.08	0.05	0.04	0.05	0.04	0.04	0.05	0.03	0.06	0.03	0.06
Positive	0.25	0.33	0.38	0.39	0.14	0.08	0.03	0.05	−0.02	0.04	0.05	0.00	0.02	0.03	0.01	0.02
Pos - neg	0.40	0.59	0.69	0.57	0.14	0.04	0.01	−0.01	−0.04	−0.02	0.08	−0.02	−0.04	0.02	−0.04	0.00
Pos - neg (cum)					0.14	0.18	0.19	0.19	0.15	0.13	0.21	0.20	0.16	0.18	0.14	0.14
Panel C: ST percent bear tweets (0%=positive, 100%=negative)																
Negative	−0.05	−0.15	−0.54	−0.86	0.00	0.06	0.05	0.06	0.05	0.05	0.03	0.05	0.05	0.03	0.05	0.06
Neutral	0.18	0.23	0.22	0.08	−0.09	−0.04	−0.03	−0.04	−0.04	−0.03	−0.02	−0.02	−0.02	−0.01	−0.01	−0.01
Positive	0.16	0.21	0.51	0.65	0.06	0.04	0.02	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.03	0.04
Pos - neg	0.21	0.36	1.05	1.51	0.06	−0.02	−0.03	−0.03	−0.02	−0.02	0.00	−0.03	−0.03	−0.01	−0.02	−0.03
Pos - neg (cum)					0.06	0.04	0.01	−0.02	−0.03	−0.05	−0.05	−0.08	−0.11	−0.12	−0.14	−0.17
Panel D: ST percent negative words (bottom 20%=positive, top 20%=negative)																
Negative	−0.03	−0.01	−0.06	−0.17	−0.04	−0.01	−0.01	−0.01	−0.02	−0.01	0.01	−0.01	−0.01	−0.02	0.00	−0.02
Neutral	0.13	0.19	0.46	0.60	−0.03	−0.03	−0.02	0.00	0.00	−0.01	0.00	−0.01	0.00	−0.01	−0.02	0.00
Positive	0.09	0.09	0.16	0.15	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.03	0.04
Pos - neg	0.11	0.10	0.22	0.32	0.10	0.06	0.05	0.05	0.06	0.05	0.03	0.05	0.05	0.07	0.04	0.06
Pos - neg (cum)					0.10	0.16	0.21	0.26	0.32	0.37	0.40	0.45	0.50	0.57	0.61	0.67
Panel E: RavenPack ESS inverted (bottom 20%=positive, top 20%=negative)																
Negative	0.02	−0.02	−0.16	−0.52	0.02	0.03	0.05	0.06	0.06	0.05	0.06	0.06	0.06	0.05	0.05	0.05
Neutral	0.07	0.06	0.06	0.08	0.06	0.06	0.05	0.06	0.05	0.04	0.05	0.04	0.06	0.06	0.06	0.07
Positive	0.12	0.19	0.40	0.81	0.06	0.06	0.05	0.05	0.06	0.06	0.06	0.05	0.05	0.06	0.05	0.05
Pos - neg	0.10	0.20	0.56	1.33	0.04	0.03	0.00	−0.01	0.00	0.01	0.00	0.00	−0.01	0.01	−0.01	0.00
Pos - neg (cum)					0.04	0.08	0.08	0.06	0.07	0.08	0.08	0.08	0.07	0.08	0.08	0.07

[7] We also use the different cut offs 100%/0%, 99%/1%, 90%/10% which provide us with very similar results.

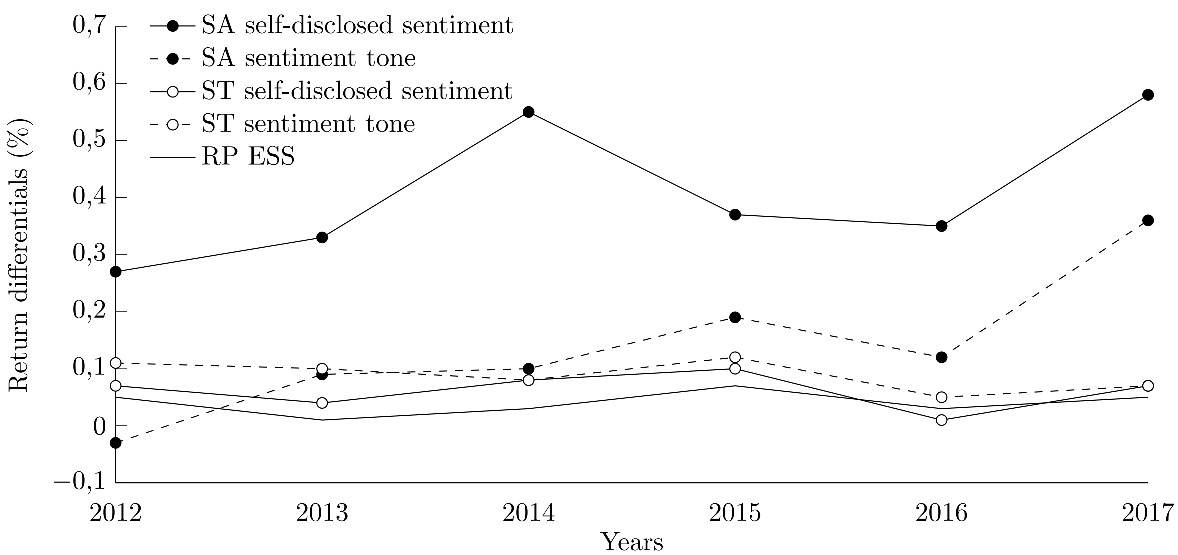
First of all it can be observed that the portfolio return differences are very high for day 0 in all five panels. The reason behind this is obvious as well performing stocks receive more favorable sentiments and vice versa. The causality between both measures is, however, not identifiable. Going to the right from the column of day 0 only sentiment can be cause and future returns are the effects. The opposite holds to the left where lagged returns are the cause and sentiment is the effect. Going to the right from day zero, thus considering the effect of sentiment on future returns, considerable differences between our analysed sentiment measures and sources become apparent. The one day ahead return difference of self-disclosed SA sentiment is very high with 0.40% both compared to all other measures and sources as well as in absolute terms, yielding an annualized return difference of 175.55%. Considering that the mean daily return of all CRSP stocks is 0.03% (7.88% per annum) during the same period (see Table 4.2) this return is one magnitude larger. Also, the return difference seems to be driven by the negative portfolio which alone provides a return of −0.28% per day. So even comparing the mean return of the negative portfolio to the mean return of all CRSP stocks still yields a daily return difference of 0.31%.

Figure 4.1 shows the day ahead return differentials of our different sentiment measures over the years. This is to show the persistence over time and to address the concern that the results could be driven by specific years. We see relatively stable differentials and particularly self-disclosed sentiment from SA consistently outperforms the other sentiment measures. For sentiment tone from SA there seems to be a development towards higher return differentials. All other measures stay relatively constantly close to zero.

Figure 4.2 illustrates the cumulative return differentials of Table 4.3. Returns on day +1 for SA self-disclosed sentiment is markedly higher than the other sentiment measures and there is no evidence of reversion to fundamentals in the days following. According to Tetlock, 2007, a reversal is often an indication that stock returns are driven by irrational investor sentiment rather than new price-relevant information. The reversal arises when rational investors arbitrage away the sentiment effect by buying from or selling to noise and liquidity traders. The persistence of our observed sentiment effect could suggest that self-disclosed sentiment from SA contains price-relevant information not yet priced into the stock valuation by investors. As deviations from fundamental values can, however, persist over long horizons (see, e. g., De Long, Shleifer, Summers, and Waldmann, 1990) it cannot be ruled out that a possible misvaluation is corrected at a later point. Chen, De, Hu, and Hwang, 2014 in their examination of the medium-term sentiment effect of SA found no reversal, deducing that SA may contain value-relevant information. We observe that SA self-disclosed sentiment reveals a persistent increase until day +10 whereas SA sentiment tone remains stable during the same period. After 12 days SA self-disclosed sentiment is at 1.09% which translates to

25.68% per annum. For self-disclosed sentiment from ST, on the other hand, a return reversal is shown in the three days following day 0, which suggests that ST self-disclosed sentiments may be related to noise and liquidity trading. An opposite pattern is found for ST sentiment tone but results based on this measure may be inconclusive because StockTwits posts are restricted to 140 characters for our sample period. Hence the ability for all price-relevant information to be fitted into one post is expected to be greatly diminished, and thereby introduce biases (and inaccuracies) into the measure.

Figure 4.1: Sentiment Portfolio Return Differentials Over Years.
This figure shows the mean return differentials of day +1 for different years. The portfolios are formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. For the definition of the variables please refer to Table 4.3.

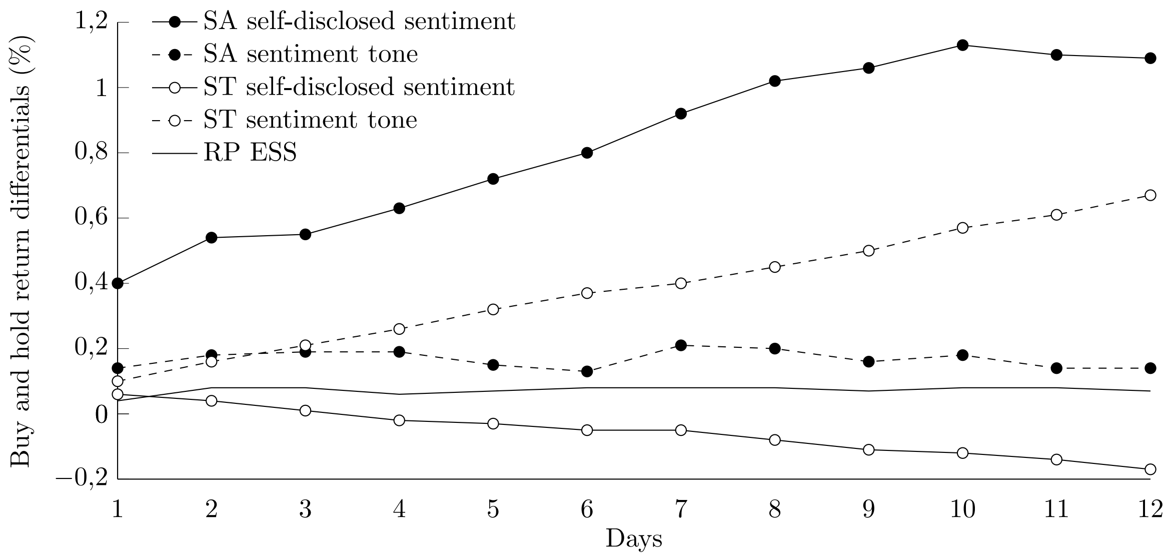


Our results so far can be summarized as follows. We observe a sentiment effect on returns, which is considerably strong for self-disclosed sentiment from SA, and predominantly driven by the negative sentiment portfolio. In general, we have two possible explanations why a sentiment effect could arise. In case that prices are moved by rational traders new price-relevant information is factored in. In case that prices are moved by noise traders irrational beliefs affect returns. It is hard to distinguish between the two. Although we see that the sentiment effect is quite persistent over the following 12 days, we do not know whether it resolves afterwards and even if it did, it could still be driven by irrational sentiment.

With regard to the importance of the negative portfolio relative to the positive portfolio of SA self-disclosed sentiment it has to be noted that negative sentiment is assigned considerably less often than positive.[8] Put differently, there is a positive bias of investor sentiments expressed on social media. This might be connected to the observed asymmetric sentiment

[8] 8.67% of all self-disclosed articles from SA and 17.31% for ST tweets are self-disclosed as negative.

Figure 4.2: Sentiment Portfolio Return Differentials Over Different Holding Periods.
This figure shows the mean buy and hold return differentials for different holding periods from a one day holding period (+1d until +1d) to a holding period of 12 days (+1d until +12d). The portfolios are formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. For the definition of the variables please refer to Table 4.3



effect in two different ways depending on the presumed investor type. If prices are moved by rational traders, negative information measured by negative sentiments might be on average of higher relevance than positive information measured by positive sentiments. If prices are moved by noise traders, irrational negative sentiments measured by self-disclosed negative sentiment might be absolutely stronger than positive sentiments measured by positive self-disclosed sentiment. To answer the question which effect is more important it again comes down to differentiating between noise and rational traders.

An interesting result of our study is that it seems as if our three sentiment sources SA, ST, and RP behaved very differently. The self-disclosed sentiment from SA by far outperforms all other sentiment sources with its prediction of one day ahead stock returns. There are three possible explanations why this sentiment effect arises. First, in the case that prices are moved by rational traders, SA contains new price-relevant information before it is factored into the stock price, while ST and RP do not. Second, in the case that prices are moved by noise traders, SA, ST, and RP may be used by separate groups of investors and only the irrational sentiment of SA users is representative of a group of investors with enough market power that actually moves stock prices. Third, the out-performance of SA self-disclosed sentiment may also arise because the means of measurement, i. e., self-disclosure, works considerably better for SA than it does for ST. This explanation is possible assuming both, rational traders or noise traders. Although it is hard to differentiate between the possible reasons, the persistence of our sentiment effect, i. e., the lack of a return reversal, indicates price-relevant informational content in SA self-disclosed sentiment. With respect to the usefulness of self-disclosed sentiment, on ST it does not provide a better performance than media tone. On the contrary, considering returns over a longer time horizon of 12 days ahead the media tone measure performs better than the self-disclosed measure. One could argue that the markedly different characteristics of SA and ST contents are important reasons for the observed differences. There are considerably more ST tweets than SA articles, SA articles are distinctly longer and more structured than tweets, and articles are moderated for quality.[9] To put it more concisely, ST is more quantity oriented while SA is more driven by quality. In this vein, self-disclosed sentiment may be very valuable in a quality driven context for predicting stock returns while it is not in a quantity-driven one.

In the right environment self-disclosed sentiment seems to be very powerful for return prediction. But why is this the case? On SA the revenues authors generate from their articles depend on their reputation. This incentives authors to be more careful and meticulous about their recommendations and holds authors accountable. On ST, content is far less structured and it is much more difficult to track the success of users' buy or sell recommendations. Furthermore, the barrier to making a contribution is higher on SA compared to ST. Publishing an article is connected to much more effort than publishing a tweet, as articles are longer, more structured, and also reviewed for quality by the platform. It is therefore that the average recommendations on SA are probably much better though-out than the average ST tweet. It is possibly for these reasons that self disclosure on SA filters noise from sentiment information providing a better measure of those sentiments that actually move share prices.

4.4.2 Portfolios according to firm size and valuation

To better understand the origins of the observed sentiment effect on the day ahead stock return we subdivide our portfolios according to firm size (Table 4.4) and valuation (Table 4.5). As before the portfolios are formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. In a second step, each of these three portfolios is subdivided into three further portfolios based on terciles of the firms' previous year end market value and book-to-market value, respectively. In Table 4.4 it can be seen that for all sentiment measures the sentiment effect is more pronounced for small stocks. The sentiment effect for self-disclosed sentiment, which is 0.40% for all stocks, increases to 0.88% if only the stocks below the first size tercile are considered. Looking at the close to zero self-disclosed return differences between the positive and negative portfolios for medium and

[9] SA: 37 articles per day with 820 words on average. ST: 14,283 tweets per day with 104 words on average

large sized firms it becomes clear that the sentiment effect of SA is almost entirely driven by the small stocks in the portfolio. The difference of daily returns is enormous and translates into a difference of 817.66% per annum. Also sentiment tone from SA yields a sizeable return difference of 0.34% for the small sentiment portfolios. For all sentiment measures the predictive power of sentiment seems to be entirely driven by the small firms in the portfolio. Something similar can be seen for firm valuation (Table 4.5), where sentiment returns are higher for value firms (firms with a low valuation, i. e., high book-to-market value). This effect is not as consistent for all sentiment sources and much more moderate in magnitude in comparison to the size effect.

To see how size affects the sentiment effect beyond what we could see using terciles we also use deciles. The return differentials are shown in Figure 4.3. In contrast to our size terciles this time we first sort all CRSP firms into size deciles based on the previous year end's market value. Only in a second step, the portfolios are then formed based on the sentiment on day 0. This way the size cut offs are representative of all CRSP firms rather than only for those in the respective sentiment portfolio. We see that particularly for self-disclosed sentiment from SA the size effect is quite consistent beyond size terciles. The curve becomes very flat slightly above zero for stocks above the 8th decile. For smaller stocks the curve increases quite consistently as size decreases. Stocks smaller than the 1st decile show an average return difference of 3.25% per day equalling 3,266.27% per annum. It has to be noted that by sorting first on firm size and then on sentiment the portfolios for the small sized stocks become very small. For the negative sentiment portfolio for instance, a total of 1,987 observations, or 38% of all negative sentiment observations, are in the largest size portfolio. The smallest size portfolio has only a total of 59 stock-day observations in it, the second smallest 123, the third smallest 167, and the fourth smallest 254. These returns therefore cannot be observed every day. This exercise nevertheless highlights the importance firm size has on the sentiment effect and what kind of returns it is able to produce. On the other hand this exercise also shows that our previously observed sentiment return differentials are not only driven by the very smallest stocks but are quite consistent and sizeable for CRSP stocks below the 8th size decile, which are by no means very small stocks.

One reason for the fact that the sentiment effect is so concentrated among small stocks maybe that the distribution of information about small stocks is more inefficient. In an inefficient and asymmetric informational context investor sentiment may play a more important role. For a rational investor this means that price-relevant information may diffuse more slowly and therefore cause a lagged reaction. For an irrational investor the fewer information about a firm is available the more is left to the investor's imagination which then makes her more sensitive to sentiment. Another explanation is given by Tetlock, 2007 who also finds

Table 4.4: Portfolios According to Sentiment and Firm Size.

This table shows the mean daily returns of different portfolios on day +1. The portfolios are formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. In a second step, each of these three portfolios is subdivided into three further portfolios based on terciles of the firm's previous year end's market value. To ensure that all observations have equal weights, each stock is bought with the same amount and the portfolios are value-weighted. For each Panel the rows one to three show the mean daily portfolio returns of the three different firm size portfolios, as well as the mean portfolio sizes. Row four shows the mean daily return differential between the positive and the negative portfolio as well as the total portfolio size. The different panels relate to different sentiment sources for the classification of negative, neutral, and positive sentiment. Panel A shows the portfolio returns based on SA for the percentage of bear articles from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day, as positive if there are 0% short articles, and as neutral for all percentages in-between. Panel B uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel C shows the portfolio returns based on ST for the percentage of bear tweets from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day, as positive if there are 0% bear tweets, and as neutral for all percentages in-between. Panel D uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel E shows mean portfolio returns bases on the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day, as positive if it is in the bottom 20%, and else neutral.

	Mean returns +1d					Portfolio sizes			
	Small	Med.	Big	S−B		Small	Med.	Big	Total
Panel A: Seeking Alpha percent short articles (0%=positive, 100%=negative)									
Negative	−0.64	0.01	0.00	−0.64	Negative	2,141	1,881	1,149	5,171
Neutral	−1.34	0.11	−0.02	−1.32	Neutral	98	350	690	1,138
Positive	0.24	0.06	0.06	0.18	Positive	21,800	21,283	21,180	64,263
Pos - neg	0.88	0.05	0.06	0.82	Total	24,039	23,514	23,019	70,572
Panel B: Seeking Alpha percent negative words (bottom 20%=positive, top 20%=negative)									
Negative	−0.03	−0.01	0.06	−0.09	Negative	4,734	4,856	4,412	14,002
Neutral	0.16	0.09	0.06	0.10	Neutral	14,681	14,069	14,045	42,795
Positive	0.31	0.04	0.04	0.27	Positive	4,613	4,579	4,553	13,745
Pos - neg	0.34	0.05	−0.02	0.36	Total	24,028	23,504	23,010	70,542
Panel C: ST percent bear messages (0%=positive, 100%=negative)									
Negative	−0.07	−0.01	0.05	−0.12	Negative	20,002	30,877	35,828	86,707
Neutral	−0.33	0.00	0.04	−0.37	Neutral	60,003	57,181	74,809	191,993
Positive	0.09	0.04	0.03	0.06	Positive	204,787	196,284	173,261	574,332
Pos - neg	0.16	0.06	−0.01	0.18	Total	284,792	284,342	283,898	853,032
Panel D: ST percent negative words (bottom 20%=positive, top 20%=negative)									
Negative	−0.15	0.01	0.03	−0.18	Negative	182,801	153,070	179,692	515,563
Neutral	−0.21	0.00	0.06	−0.26	Neutral	68,077	60,154	108,372	236,603
Positive	0.05	0.06	0.06	−0.01	Positive	632,174	669,541	594,341	1,896,056
Pos - neg	0.19	0.06	0.03	0.16	Total	883,052	882,765	882,405	2,648,222
Panel E: RavenPack ESS inverted (bottom 20%=positive, top 20%=negative)									
Negative	0.01	0.04	0.06	−0.05	Negative	89,847	111,156	103,304	304,307
Neutral	0.08	0.07	0.07	0.01	Neutral	277,442	344,103	426,376	1,047,921
Positive	0.07	0.07	0.07	0.00	Positive	76,712	78,884	100,028	255,624
Pos - neg	0.06	0.03	0.01	0.05	Total	444,001	534,143	629,708	1,607,852

that negative sentiment seems to have a longer-lasting and larger impact on small stocks over the short-term. The author's explanation is that small stocks have higher individual investor ownerships. In this vein, if our sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks better.

Table 4.5: Portfolios According to Sentiment and Firm Valuation.
This table shows the mean daily returns of different portfolios on day +1. The portfolios are formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. In a second step, each of these three portfolios is subdivided into three further portfolios based on terciles of the firm's previous year end's book-to-market value. To ensure that all observations have equal weights, each stock is bought with the same amount and the portfolios are value-weighted. For each Panel the rows one to three show the mean daily portfolio returns of the three different book-to-market portfolios, as well as the mean portfolio sizes. Row four shows the mean daily return differential between the positive and the negative portfolio as well as the total portfolio size. The different panels relate to different sentiment sources for the classification of negative, neutral, and positive sentiment. Panel A shows the portfolio returns based on SA for the percentage of bear articles from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day, as positive if there are 0% short articles, and as neutral for all percentages in-between. Panel B uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel C shows the portfolio returns based on ST for the percentage of bear tweets from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day, as positive if there are 0% bear tweets, and as neutral for all percentages in-between. Panel D uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%, and else neutral. Panel E shows mean portfolio returns bases on the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day, as positive if it is in the bottom 20%, and else neutral.

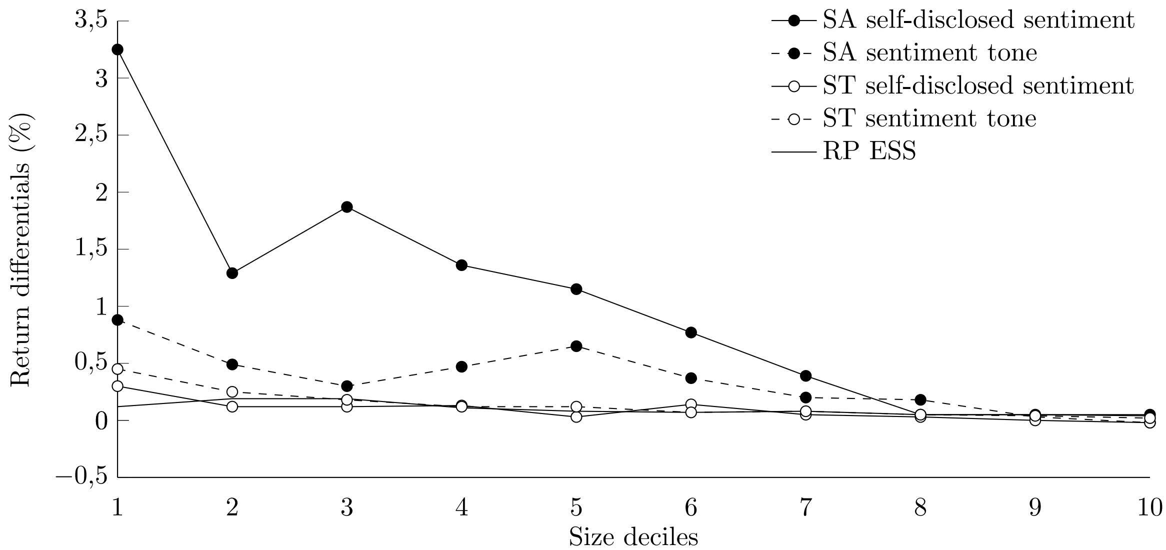
	Mean returns +1d					Portfolio sizes			
	Low	Med.	High	H−L		Low	Med.	High	Total
Panel A: Seeking Alpha percent short articles (0%=positive, 100%=negative)									
Negative	−0.15	−0.27	−0.33	−0.19	Negative	2,212	1,426	1,303	4,941
Neutral	0.01	−0.29	0.31	0.30	Neutral	683	293	140	1,116
Positive	0.15	0.09	0.14	0.00	Positive	20,341	21,035	20,800	62,176
Pos - neg	0.29	0.36	0.48	0.18	Total	23,236	22,754	22,243	68,233
Panel B: Seeking Alpha percent negative words (bottom 20%=positive, top 20%=negative)									
Negative	0.12	−0.07	0.02	−0.10	Negative	4,268	4,010	5,147	13,425
Neutral	0.10	0.08	0.16	0.06	Neutral	14,457	13,883	13,092	41,432
Positive	0.16	0.15	0.10	−0.06	Positive	4,500	4,853	3,996	13,349
Pos - neg	0.04	0.22	0.08	0.04	Total	23,225	22,746	22,235	68,206
Panel C: ST percent bear messages (0%=positive, 100%=negative)									
Negative	0.00	0.05	−0.03	−0.03	Negative	20,970	25,687	25,857	72,514
Neutral	−0.03	−0.08	−0.09	−0.06	Neutral	66,918	49,420	47,305	163,643
Positive	0.06	0.07	0.08	0.01	Positive	164,147	176,468	177,951	518,566
Pos - neg	0.06	0.02	0.11	0.05	Total	252,035	251,575	251,113	754,723
Panel D: ST percent negative words (bottom 20%=positive, top 20%=negative)									
Negative	−0.03	−0.01	−0.04	−0.01	Negative	165,410	127,434	138,126	430,970
Neutral	−0.02	0.00	−0.05	−0.03	Neutral	93,328	60,350	55,540	209,218
Positive	0.07	0.06	0.06	−0.01	Positive	515,055	585,598	579,125	1,679,778
Pos - neg	0.10	0.07	0.10	0.01	Total	773,793	773,382	772,791	2,319,966
Panel E: RavenPack ESS inverted (bottom 20%=positive, top 20%=negative)									
Negative	0.04	0.05	0.04	0.00	Negative	101,980	101,226	91,665	294,871
Neutral	0.07	0.07	0.08	0.01	Neutral	358,528	346,916	314,303	1,019,747
Positive	0.07	0.06	0.09	0.02	Positive	91,523	82,387	74,468	248,378
Pos - neg	0.03	0.01	0.05	0.02	Total	552,031	530,529	480,436	1,562,996

4.4.3 Portfolio characteristics

Table 4.6 shows different characteristics of the portfolios used in Table 4.3. Looking at the total column we can compare the selection of firms covered by the respective sentiment source. There are two noticeable differences. First, stocks covered by SA are considerably

Figure 4.3: Daily Portfolio Return Differentials According to Sentiment and Firm Size Deciles.

This figure shows the mean return differentials on day +1 for different market value deciles. The firms are first sorted into deciles based on the previous year end's market value. In a second step, the portfolios are then formed based on the sentiment on day 0, which is classified into three categories, negative, neutral, and positive. For the definition of the variables please refer to Table 4.3.



larger on average than for ST and RP. Keeping in mind that SA also has distinctly less content than the others it also seems to focus on larger firms. The second interesting result is that the self-disclosure on ST seems be applied to entirely different firms than all other measures. The average return on assets as well as past year's buy and hold abnormal return are considerably more negative than for all other sentiment measures. The opposite holds for the idiosyncratic volatility which is distinctly higher. It seems that predominantly stocks with a poor past performance and high volatility are labelled with a self-disclosed sentiment on ST.

In comparing the negative sentiment portfolios with the positive sentiment portfolios we see that for all measures the firms in the negative portfolios have had a lower return on assets in the preceding year. However, this is not true for the self-disclosed sentiment of ST where interestingly it is the other way around and stock self-disclosed as bullish exhibited considerably lower returns on assets. Taking a closer look at the the self-disclosure of SA which gives us by far the best results in predicting stock returns we see two major differences between the positive and negative portfolios. The first one is the aforementioned lower past year's profitability of the negative portfolio firms. The second one is that firms in the negative portfolio are on average half the size of those in the positive portfolio. Firms in the negative SA self-disclosed portfolio are therefore comparatively smaller and have a poorer recent operating performance.

Table 4.6: Portfolio Characteristics.
This table shows the mean characteristics of the different sentiment portfolios. Observations is the total number of firm returns in the respective portfolio. Market value is a firm's market value in thousand US-$, Book-to-market is the ratio of a firm's book and market value, and Return on assets is a firm's yearly net income divided by its total assets. Market value, Book-to-market, and Return on assets all relate to their respective values at the previous year end. The Buy and hold abnormal return is the cumulated abnormal return calculated with the Fama French Five Factor Model over the preceding 252 trading days and the Idiosyncratic volatility is the abnormal return's standard deviation over the preceding 252 trading days. Return -1d, Return, and Return +1d are the total return calculated with daily closing prices and corrected for dividend payments one day prior to portfolio formation, on the day of portfolio formation, and one day after portfolio formation, respectively.

	Negative	Neutral	Positive	Total
Panel A: Seeking Alpha percent short articles (0%=positive, 100%=negative)				
Observations	5,394	1,174	65,402	71,970
Market cap	25,736,629.20	120,977,390.74	47,517,082.02	47,109,256.01
Book-to-market	0.73	0.43	0.96	0.94
Return on assets (%)	−4.79	0.89	−0.98	−1.23
Buy and hold abnormal return (%)	−5.48	−3.79	−5.38	−5.36
Idiosyncratic volatility (%)	2.98	2.40	2.29	2.34
Panel B: Seeking Alpha percent negative words (bottom 20%=positive, top 20%=negative)				
Observations	14,216	43,696	14,058	71,970
Market cap	42,434,910.86	50,090,598.08	42,587,101.69	47,109,256.01
Book-to-market	1.17	0.91	0.81	0.94
Return on assets (%)	−2.48	−1.71	1.52	−1.23
Buy and hold abnormal return (%)	−10.50	−4.90	−1.62	−5.36
Idiosyncratic volatility (%)	2.51	2.36	2.13	2.34
Panel C: ST percent bear messages (0%=positive, 100%=negative)				
Observations	87,356	195,195	583,114	865,665
Market cap	13,682,104.41	22,322,626.11	11,106,511.81	13,896,485.31
Book-to-market	1.25	0.78	1.09	1.04
Return on assets (%)	−5.30	−22.28	−13.82	−14.84
Buy and hold abnormal return (%)	−7.95	−13.97	−8.28	−9.53
Idiosyncratic volatility (%)	2.55	4.18	3.23	3.38
Panel D: ST percent negative words (bottom 20%=positive, top 20%=negative)				
Observations	522,926	239,216	1,914,798	2,676,940
Market cap	11,913,397.83	23,447,943.89	6,825,917.36	9,303,370.01
Book-to-market	1.15	0.78	1.31	1.23
Return on assets (%)	−12.23	−13.47	−3.05	−5.69
Buy and hold abnormal return (%)	−10.24	−7.08	−4.53	−5.87
Idiosyncratic volatility (%)	3.12	3.21	2.25	2.51
Panel E: RavenPack ESS inverted (bottom 20%=positive, top 20%=negative)				
Observations	443,716	1,460,147	382,471	2,286,334
Market cap	7,382,693.69	11,174,171.55	11,466,556.54	10,482,784.70
Book-to-market	1.66	1.54	1.86	1.62
Return on assets (%)	−0.08	0.40	−1.37	0.01
Buy and hold abnormal return (%)	−6.55	−3.75	−1.47	−3.91
Idiosyncratic volatility (%)	2.13	2.00	2.20	2.06

4.5 Explaining sentiment returns

So far we have seen the different returns of portfolios based on our investor sentiment measures. In a next step we will show in which way common risk factors may be able to explain our observed effects. For this we use two different approaches: time series factor regressions as well as abnormal return regressions.

4.5.1 Explaining sentiment returns with common risk factors

An obvious question is whether our observed sentiment effects are actually driven by common risk factors rather than investor sentiment. This could be the case if investor sentiment is dependent on firm characteristics like size and valuation which are known to be common risk factors. This way sentiment may choose stocks which predominantly load on these factors thereby giving the impression of a sentiment effect which is actually a disguised common risk premium. We form long-short portfolios on a daily basis that long stocks with a positive sentiment on the preceding day and short stocks with a negative sentiment. Table 4.7 shows the estimation results of five factor regressions on these sentiment long-short portfolios. The risk factors used as independent variables are the five Fama & French risk factors, market (*MKT-RF*), size (*SMB*), valuation (*HML*), profitability (*RMW*), and investment (*CMA*) (Fama and French, 1993; Fama and French, 2015). If sentiment can explain the day ahead stock return beyond known common risk factors we have to find significant alphas in these regressions representing that part of the long-short portfolio that cannot be explained by common risk factors.

Four of our five regressions have highly significant alphas showing the presence of a sentiment effect. The only long-short portfolio that only has a weakly significant alpha is the one formed on the basis of self-disclosed sentiment from ST. When we compare the magnitude of the intercepts with our results from the portfolio analysis in the previous chapter we see that they are very similar. This means that common risk factors explain only a very small part of the observed sentiment return. This can also be seen looking at the R^2 values which are generally small and particularly small for SA. Distinctly higher R^2 can be seen for ST and RP. This suggests that common risk factors explain the long-short portfolio returns to some degree, although for ST sentiment tone and the RP ESS a significantly positive sentiment return remains.

In Table 4.8 we show the alphas of different stock portfolios based on specific characteristics. As usual the stocks are first categorized into three categories according to sentiment and in second step each portfolio is subdivided into three portfolios according to the terciles of the following characteristics: firm size, valuation, previous day's stock return, previous year's buy and hold abnormal return, as well as previous year's idiosyncratic volatility. This analysis in the spirit of Fang and Peress, 2009 allows us to do two things. First, we can see among which firms the sentiment effect is the strongest. Second, we also control for the respective characteristic. If the sentiment effect were in fact only a disguised sort on these characteristics we would expect the alphas to become insignificant in each tercile because the stocks within each tercile are more similar in terms of this characteristic. Panel A shows the

Table 4.7: Five Factor Regressions on Sentiment Long-Short Portfolios.
This table shows the results of time series factor regressions on different sentiment long-short portfolios. All long-short portfolios go long on positive sentiment stocks on the preceding day and short on negative sentiment stocks. LSP SA % short articles is based on the percentage of short articles on SA from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day, as positive if there are 0% short articles. LSP SA % neg. words uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%. LSP ST % bear tweets uses the percentage of bear tweets on ST from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day, as positive if there are 0% bear tweets. LSP ST % neg. words uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%. LSP RP ESS uses the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day, as positive if it is in the bottom 20%. The five factors used as independent variables are the five Fama & French risk factors, market (MKT-RF), size (SMB), valuation (HML), profitability (RMW), and investment (CMA). t-Statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	LSP SA % short articles	LSP SA % neg. words	LSP ST % bear tweets	LSP ST % neg. words	LSP RP ESS inverted
MKT-RF	−0.039	−0.068	0.026	−0.018*	−0.069***
	(−0.497)	(−1.318)	(0.834)	(−1.734)	(−7.150)
SMB	−0.047	−0.195**	0.219***	−0.022	−0.111***
	(−0.396)	(−2.399)	(4.492)	(−1.305)	(−7.330)
HML	−0.179	−0.351***	−0.127**	0.104***	−0.061***
	(−1.207)	(−3.476)	(−2.081)	(5.057)	(−3.260)
RMW	−0.522***	−0.045	−0.236***	0.317***	−0.033
	(−2.759)	(−0.344)	(−3.032)	(11.938)	(−1.388)
CMA	0.489**	0.061	−0.313***	−0.044	−0.025
	(2.080)	(0.380)	(−3.209)	(−1.345)	(−0.822)
Constant	0.394***	0.143***	0.041*	0.079***	0.046***
	(7.165)	(3.925)	(1.859)	(10.606)	(6.778)
Observations	1,108	1,508	1,374	1,509	1,509
R2	0.010	0.018	0.065	0.129	0.098

alphas of portfolios sorted on firm size. As could already be seen in the descriptive portfolio analysis, the sentiment effect is the strongest for small stocks and considerably smaller to non significant for medium and large stocks. This is particularly the case for SA which produces enormous alphas for small stocks. It is, as mentioned before, important to interpret long-short portfolio returns correctly. The fact that the effect is strongest among small stocks speaks to the fact that it is not a disguised size effect since it is stronger among more evenly sized firms. The factor analysis further shows that risk factors cannot explain a relevant portion of this sentiment effect within the small firms subsample. While the SA sentiment effect is practically limited to small stocks, also for ST and RP we see a tilt towards higher sentiment returns of smaller stocks but also medium and large size firms exhibit a sentiment effect. Panel B shows the alphas of portfolios sorted on firm valuation. For SA there seems to be a tilt towards higher returns for value firms. The sentiment effect is however, more evenly distributed across firm valuations. Panel C shows the alphas of portfolios sorted on the preceding day's return. We choose this measure to address the concern that the sentiment effect on the following day's stock return is actually due to auto-correlation of returns. This is an intuitive concern as sentiment is highly dependent on contemporaneous stock returns. The results clearly show that the alphas are generally very comparable in size and significances for all return terciles. This is to say that the past return plays no important role for the sentiment effect. Panel D shows the alphas for portfolios sorted on the preceding 252 trading days' buy and hold abnormal return calculated with the Fama and French five factor model. As for the past day's return the sentiment effect seems not to be clustered with regard to this measure for all sentiment measures. Panel D shows the alphas for portfolios sorted on the idiosyncratic volatility calculated as the abnormal return's standard deviation over the preceding 252 trading days. Volatility seems to be of comparable importance as firm size with high volatility firms exhibiting a much larger sentiment effect.

The sentiment effect seems to be generally quite heterogeneous across firm size and idiosyncratic volatility, with small firms and high volatility stocks having a considerably more pronounced sentiment effect. We before gave higher informational asymmetry and higher shares of individual ownership around small stocks as possible explanations for the size effect. Both reasons also relate to stock volatility. Stocks with higher informational asymmetry should consequently have a larger idiosyncratic volatility since their valuation changes with the information investors posses. Also, higher shares of individual investor ownership are connected to higher degrees of idiosyncratic volatility because individual investors behave as noise traders (e. g., Storey et al., 2007). Therefore, the sentiment effect's concentration among high volatility stocks may also tentatively speak to the importance of noise trading for the sentiment effect. However, although higher shares of individual investor ownership are connected to higher degrees of idiosyncratic volatility, it cannot be concluded that the effect of volatility on our sentiment effect is due to noise trading.

Table 4.8: Five Factor Regression Alphas of Regressions on Sentiment and Firm Characteristic Portfolios.

This table shows the constants of time series factor regressions on different sentiment long-short portfolios. All long-short portfolios go long on positive sentiment stocks on the preceding day and short on negative sentiment stocks. The stocks are first categorized into three categories according to sentiment and in second step each portfolio is subdivided into three portfolios according to the terciles of the following characteristics: Previous year end market value (Panel A), previous year end Book-to-market-value (Panel B), previous day's stock return (Panel C), the Buy and hold abnormal return (BHAR) calculated with the Fama French Five Factor Model over the preceding 252 trading days (Panel D) and the Idiosyncratic volatility as the abnormal return's standard deviation over the preceding 252 trading days (Panel E). LSP SA % short articles is based on the percentage of short articles on SA from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day, as positive if there are 0% short articles. LSP SA % neg. words uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%. LSP ST % bear tweets uses the percentage of bear tweets on ST from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day, as positive if there are 0% bear tweets. LSP ST % neg. words uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day, as positive if it is among the bottom 20%. LSP RP ESS uses the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day, as positive if it is in the bottom 20%. The five factors used as independent variables are the five Fama & French risk factors, market (MKT-RF), size (SMB), valuation (HML), profitability (RMW), and investment (CMA). t-Statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	LSP SA % short articles	LSP SA % neg. words	LSP ST % bear tweets	LSP ST % neg. words	LSP RP ESS inverted
Panel A: Size terciles					
Small	0.882***	0.337***	0.080**	0.151***	0.077***
	(7.554)	(3.666)	(2.220)	(6.753)	(4.620)
Medium	0.057	0.062	0.050**	0.033**	0.033***
	(0.766)	(1.033)	(2.086)	(2.476)	(2.727)
Big	0.025	−0.009	0.036**	0.008	0.018**
	(0.399)	(−0.246)	(2.422)	(0.852)	(2.147)
Panel B: Book-to-market terciles					
Low	0.299***	0.057	0.073***	0.077***	0.037***
	(3.576)	(0.748)	(2.791)	(3.934)	(3.211)
Medium	0.398***	0.230***	−0.020	0.057***	0.016
	(3.992)	(3.637)	(−0.806)	(4.126)	(1.497)
High	0.600***	0.126*	0.073***	0.082***	0.058***
	(5.197)	(1.873)	(3.012)	(5.118)	(4.344)
Panel C: Return terciles					
Low	0.490***	0.243***	0.029	0.085***	0.054***
	(5.273)	(3.291)	(1.260)	(4.688)	(3.952)
Medium	0.212***	0.165***	0.020	0.030**	0.050***
	(3.079)	(3.255)	(1.116)	(2.394)	(5.645)
High	0.544***	0.187**	0.052*	0.074***	0.036***
	(5.166)	(2.322)	(1.914)	(4.678)	(2.879)
Panel D: Buy and hold abnormal return terciles					
Low	0.494***	0.116	0.043	0.082***	0.041***
	(4.654)	(1.408)	(1.611)	(4.213)	(2.753)
Medium	0.133*	0.133**	0.046***	0.019	0.025***
	(1.718)	(2.458)	(2.854)	(1.373)	(2.770)
High	0.500***	0.204***	0.016	0.065***	0.048***
	(5.371)	(2.844)	(0.743)	(4.827)	(4.395)
Panel E: Idiosyncratic volatility terciles					
Low	0.080**	0.028	0.025**	0.014	0.019***
	(2.016)	(0.941)	(2.073)	(1.090)	(2.790)
Medium	0.119*	0.079	0.046**	0.017	0.038***
	(1.919)	(1.383)	(2.206)	(1.139)	(4.068)
High	0.759***	0.342***	0.069**	0.098***	0.066***
	(6.435)	(3.356)	(2.277)	(5.032)	(3.914)

To further investigate in which leg of the long-short portfolios the sentiment effect is the strongest we consider five factor regressions on the long and short legs alone, see Tables 4.9 and 4.10. As could already be seen from the descriptive portfolio analysis it is clear that the sentiment effect is much more pronounced in the short leg portfolios which shows highly significant and economically large alphas for almost all sentiment measures. Considering the relevance of common risk factors for the portfolio returns especially for the self-disclosed sentiment of SA the risk factors seem to have relatively little explanatory power. This is indicated by the R^2 which is distinctly smaller than it is for the other measures particularly from the other sentiment sources ST and RP. Comparing the R^2 from the short and the long legs we see that these are generally of similar magnitude for all sentiment measures except for the measure of self-disclosed sentiment from SA. For the long leg of this measure the explanatory power increases more than 3-fold, highlighting the considerably bigger sentiment content in the short leg relative to the long leg.

Table 4.9: Five Factor Regressions on Sentiment Long Portfolios.
This table shows the results of time series factor regressions on the long leg of different sentiment long-short portfolios. All sentiment long portfolios go long on positive sentiment stocks. Long leg SA % short articles is based on the percentage of short articles on SA from all articles on a given day for a given stock. The sentiment is classified as positive if there are 0% short articles on a given day. Long leg SA % neg. words uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in the bottom 20% from all observations on that day. Long leg ST % bear tweets uses the percentage of bear tweets on ST from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as positive if there are 0% bear tweets on a given day. Long leg ST % neg. words uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as positive if the percentage of negative words from all words published on that day is in bottom 20% from all observations on that day. Long leg RP ESS uses the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as positive if the sentiment score is in the bottom 20% of all sentiment scores on that day. The five factors used as independent variables are the five Fama & French risk factors, market (MKT-RF), size (SMB), valuation (HML), profitability (RMW), and investment (CMA). t-Statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	Long leg SA % short articles	Long leg SA % neg. words	Long leg ST % bear tweets	Long leg ST % neg. words	Long leg RP ESS inverted
MKT-RF	1.027***	1.006***	0.984***	0.946***	0.943***
	(55.378)	(30.506)	(31.535)	(116.619)	(105.713)
SMB	0.401***	0.331***	0.711***	0.543***	0.493***
	(13.755)	(6.394)	(14.563)	(42.631)	(35.215)
HML	0.033	−0.117*	−0.106*	0.035**	0.023
	(0.912)	(−1.828)	(−1.733)	(2.189)	(1.346)
RMW	−0.280***	−0.252***	−0.586***	−0.217***	−0.230***
	(−6.023)	(−3.055)	(−7.550)	(−10.706)	(−10.283)
CMA	0.057	0.075	−0.132	0.021	0.031
	(0.996)	(0.728)	(−1.361)	(0.835)	(1.132)
Constant	0.075***	0.090***	−0.031	0.000	0.007
	(5.770)	(3.885)	(−1.413)	(0.053)	(1.171)
Observations	1,509	1,508	1,421	1,509	1,509
R2	0.764	0.485	0.600	0.940	0.927

Table 4.10: Five Factor Regressions on Sentiment Short Portfolios.
This table shows the results of time series factor regressions on different sentiment long-short portfolios. All long-short portfolios go long on positive sentiment stocks on the preceding day and short on negative sentiment stocks. Short leg SA % short articles is based on the percentage of short articles on SA from all articles on a given day for a given stock. The sentiment is classified as negative if there are 100% short articles on a given day. Short leg SA % neg. words uses the percentage of negative words from all words published for a given stock on a given day on SA. The sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day. Short leg ST % bear tweets uses the percentage of bear tweets on ST from all self-disclosed tweets on a given day for a given stock. Analogous to SA, the sentiment is classified as negative if there are 100% bear tweets on a given day. Short leg ST % neg. words uses the percentage of negative words from all words published for a given stock on a given day on ST. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. Analogous to SA, the sentiment of a specific stock on a given day is classified as negative if the percentage of negative words from all words published on that day is in top 20% from all observations on that day. Short leg RP ESS uses the inverted Event Sentiment Score (ESS) from RavenPack for sentiment measurement. The score corresponds to the mean inverted ESS of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. The sentiment of a stock on a given day is classified as negative if the sentiment score is in the top 20% of all sentiment scores on that day. The five factors used as independent variables are the five Fama & French risk factors, market (MKT-RF), size (SMB), valuation (HML), profitability (RMW), and investment (CMA). t-Statistics are shown in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	Short leg SA % short articles	Short leg SA % neg. words	Short leg ST % bear tweets	Short leg ST % neg. words	Short leg RP ESS inverted
MKT-RF	1.090***	1.074***	0.945***	0.964***	1.012***
	(14.137)	(25.867)	(41.584)	(64.932)	(107.498)
SMB	0.454***	0.526***	0.487***	0.565***	0.604***
	(3.842)	(8.067)	(13.547)	(24.215)	(40.865)
HML	0.181	0.234***	0.010	−0.070**	0.084***
	(1.233)	(2.888)	(0.233)	(−2.412)	(4.606)
RMW	0.220	−0.208**	−0.332***	−0.534***	−0.196***
	(1.177)	(−1.998)	(−5.808)	(−14.362)	(−8.328)
CMA	−0.313	0.014	0.218***	0.065	0.056*
	(−1.348)	(0.105)	(3.056)	(1.415)	(1.912)
Constant	−0.330***	−0.053*	−0.078***	−0.078***	−0.038***
	(−6.065)	(−1.818)	(−4.824)	(−7.536)	(−5.815)
Observations	1,108	1,509	1,400	1,509	1,509
R2	0.212	0.427	0.672	0.844	0.931

4.5.2 Explaining abnormal sentiment returns

A different approach to show the influence of investor sentiment on stock returns consists in using abnormal returns. Previously we explained long-short portfolio returns with common risk factors and looked for a significant part that could not be explained. Now we first account for common risk factors by calculating abnormal returns and then use these as the dependent variable in a regression. The estimation results can be seen in Table 4.11. The abnormal returns are calculated using the five Fama & French risk factors, market, size, valuation, profitability, and investment over an estimation period of 252 trading days starting on day -1. We then use these abnormal returns in a panel regression on firm-day level as the dependent variable and the previous day's sentiment as the independent variable of interest. Again, each column refers to a different sentiment measure. This method also allows us to control for other possible influences beyond common risk factors, like the past days' returns, past years' buy and hold abnormal return, past years' idiosyncratic volatility, year-month fixed effects, and firm fixed effects. To make the coefficients of our different sentiment measures comparable we standardize all sentiment variables to have a zero mean and variance of one. The coefficient therefore shows the change in the dependent variable if the independent variable is increased by one standard deviation. Since we have seen before that firm size plays an important role for the sentiment effect we interact the sentiment variable with binary variables for size terciles.[10] The sentiment measures are defined as percentages of negative articles/tweets, percentages of negative words, and as the inverted ESS score. This means that all sentiment measures are between 0 and 100, 0 indicating the most positive sentiment possible and 100 indicating the most negative sentiment possible. We treat all days without sentiment information as missing values, which makes samples sizes in our regressions varying. Since on SA, ST, and RP sentiment information are independently published there is not a sentiment information for every firm on every day from every sentiment source.

First of all it can be noted that for both SA measures our control variables are insignificant but for the buy and hold abnormal return from the preceding year. This variable is also significant and negative in the other three regressions. The negative influence of the $BHAR$ speaks to the existence of long-term sentiments in stock markets. Stocks that perform well over a certain period of time have a higher likelihood of under-performing afterwards. For ST and RP there is a negative dependence on the preceding days' raw returns. This is in line with the notion of auto correlation of stock returns. The fact that we do not observe this auto correlation effect for SA sentiment underlines the importance of the previous day's sentiment for the next day's stock return. Due to the inclusion of interaction terms of sentiment and firm size it is important to interpret the results correctly. The coefficient on the sentiment variable alone indicates the sentiment effect for small size firms (i. e., below the first size tercile). The coefficients of the interaction terms indicate whether medium or large size firms have a significantly different impact in comparison to small sized firms. We see a highly significant coefficient for all sentiment measures but SA sentiment tone. In line with our previous results, the effect is the largest for SA self-disclosed sentiment. Furthermore, the size effect can be seen through the significance of the sentiment variable as well as the interaction terms. For all sentiment measures the effect for medium and large size firms is significantly more positive than for small firms which exhibit significantly negative effects. Looking at the R^2 values we also see that the SA regressions exhibit distinctly higher values. This underlines the higher explanatory power of past SA sentiment for the next day's abnormal return.

[10] We use this approach instead of linearly interacting both variables since we have already seen that the size influence is clearly non-linear.

Table 4.11: Investor Sentiment and Abnormal Returns.
This table shows the results of regressions on the abnormal stock returns on day 0 on a firm-day basis. The abnormal returns are calculated using the five Fama & French risk factors, market (MKT-RF), size (SMB), valuation (HML), profitability (RMW), and investment (CMA) over an estimation period of 252 trading days starting on day −1. In each regression the control variables are $\text{Return}_{-}1$, $\text{Return}_{-}2$, and $\text{Return}_{-}3$, which are the total returns calculated with daily closing prices and corrected for dividend payments, of day −1, −2, and −3, respectively. Return on assets is a firm's yearly net income divided by its total assets. The Buy and hold abnormal return (BHAR) is the cumulated abnormal return calculated with the Fama & French Five Factor Model over the preceding 252 trading days and the Idiosyncratic volatility is the abnormal return's standard deviation over the preceding 252 trading days. Return, Return on assets, Buy and hold abnormal return, and Idiosyncratic volatility are all given in percent. Each regression also uses the lagged sentiment score of day −1 interacted with firm size terciles as the independent variables of interest. The first row shows the lagged sentiment variable, the second and third rows show this sentiment score interacted with the two binary variables Size medium and Size large, which are equal to one if the firm is in the middle and upper market value tercile, respectively. All sentiment variables are standardized to have a zero mean and variance of one. SA % short articles is the percentage of articles classified as "short" from all articles published for a specific firm on a specific day and missing if no articles exist. SA % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no articles exist. ST % bear tweets is the percentage of tweets classified as "bearish" from all self-disclosed tweets for a specific firm on a specific day and missing if no self-disclosed articles exist. ST % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no tweets exist. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. RP mean ESS (inverted) corresponds to the mean inverted Event Sentiment Score of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. t-Statistics are shown in parentheses, standard errors are clustered by firm and year-month. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	Abn. return	Abn. return	Abn. return	Abn. return	Abn. return
Return_{-1}	−0.002	0.001	−0.018***	−0.015***	−0.012***
	(−0.335)	(0.130)	(−6.151)	(−6.791)	(−5.302)
Return_{-2}	−0.001	−0.001	−0.011***	−0.007***	−0.002
	(−0.225)	(−0.147)	(−4.129)	(−3.730)	(−0.813)
Return_{-3}	−0.001	0.000	−0.008***	−0.006***	−0.005**
	(−0.113)	(−0.060)	(−3.301)	(−3.613)	(−2.201)
Return on assets	0.001	0.001	−0.002***	−0.002***	−0.002***
	(0.457)	(0.506)	(−4.093)	(−5.249)	(−4.288)
BHAR	−0.003***	−0.003***	−0.004***	−0.004***	−0.003***
	(−5.649)	(−5.807)	(−15.357)	(−17.446)	(−16.723)
Id. volatility	−0.024	−0.029	−0.079***	−0.067***	−0.039***
	(−1.361)	(−1.626)	(−13.419)	(−13.008)	(−5.283)
	SA % short articles	SA % neg. words	ST % bear tweets	ST % neg. words	RP ESS inverted
$\text{Sent. variable}_{-1}$	−0.165***	−0.051*	−0.064***	−0.019***	−0.040***
	(−5.579)	(−1.705)	(−5.766)	(−4.373)	(−7.324)
* Size medium	0.114***	0.033	0.042***	0.015***	0.026***
	(3.535)	(0.960)	(3.048)	(2.693)	(4.401)
* Size large	0.146***	0.057*	0.059***	0.013***	0.036***
	(4.565)	(1.834)	(5.617)	(2.715)	(6.217)
Constant	0.071*	0.080*	0.131***	0.108***	0.051***
	(1.704)	(1.868)	(6.407)	(7.924)	(3.571)
Observations	67,381	67,381	755,735	2,323,118	1,561,504
R-squared	0.078	0.077	0.011	0.007	0.007
Firms	3,684	3,684	4,832	5,295	4,131
Year-month FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes

4.6 Investor sentiment and liquidity

So far we have analysed the effect of today's sentiment on the next day's stock returns. We now also consider the effect on stock liquidity by looking at trading volumes and bid-ask spreads. We use the same panel regressions on firm-day level as we did in the previous chapter. As dependent variables we examine a stock's daily *Volume* (Table 4.12), which is the ratio of its daily trading volume and market capitalization, and its *Bid-ask spread* (Table 4.13), which is the difference of the highest bid and the lowest ask price relative to the ask price at the daily closing time. The independent control variables include the lagged dependent variable on day −1, *Ln(Market value)*, *Book-to-market*, and *Return on assets*. The Buy and hold abnormal return (*BHAR*) and the *Idiosyncratic volatility* are defined as before. Each regression also uses the lagged sentiment score of day −1 interacted with firm size terciles as the independent variables of interest. The first row shows the lagged sentiment variable, the second and third rows show this sentiment score interacted with the two binary variables *Size medium* and *Size large*, which are equal to one if the firm is in the middle and upper market value tercile, respectively. In contrast to the previous regressions on abnormal returns we construct two further sentiment variables for SA and ST to measure the agreement of sentiment following Antweiler and Frank, 2004. For SA this measure is defined as follows. The definition of *ST agreement* is analogous.

$$SA\ agreement = 1 - \sqrt{1 - \left(\frac{SA\ \%\ short\ articles - SA\ \%\ long\ articles}{100}\right)^2}. \qquad (4.1)$$

To ensure the comparability of coefficients, all sentiment variables are standardized to have a zero mean and variance of one.

The estimation results show a very contrasting picture to what we have seen so far for stock returns. For both liquidity measures only ST exhibits a highly significant influence. This is particularly interesting against the backdrop that both the significant sentiment measure and the agreement measure are self-disclosed. In our previous analyses we noticed that ST sentiment in general and the self-disclosed sentiment in particular had only very limited relevance for stock returns. We argued that either SA contains new price-relevant information, while ST and RP do not, or that the means of measurement, i. e., self-disclosure, works considerably better for SA than for ST. These results now show that self-disclosure as the means of measurement does in fact measure relevant investor sentiments. These sentiment are, however, related to trading activity and not to stock returns. A reason for this could be that this activity is generated by noise traders who trade among themselves or with rational traders. The lack of a significant stock movement due to this trading activity then indicates that no rational trading takes place, i. e., no new information are processed. It seems that for trading activity the quantity oriented nature of ST delivers a much better indication and the quality oriented nature of SA delivers a much better indication of stock returns.

With regard to the effect direction the coefficient for agreement for small stocks has a negative sign for volume and positive sign for bid-ask spreads. More specifically, for

Table 4.12: Investor Sentiment and Trading Volume.
This table shows the results of regressions on the trading volume on day 0 on a firm-day basis. The independent variable Volume is the ratio of a share's daily trading volume and its market capitalization. The independent control variables include the Volume on day −1, Ln(Market value) is the natural logarithm of a firm's market value in thousand US-$, Book-to-market is the ratio of a firm's book and market value, and Return on assets is a firm's yearly net income divided by its total assets. The Buy and hold abnormal return (BHAR) is the cumulated abnormal return calculated with the Fama French Five Factor Model over the preceding 252 trading days and the Idiosyncratic volatility is the abnormal return's standard deviation over the preceding 252 trading days. Volume, Return on assets, Buy and hold abnormal return, and Idiosyncratic volatility are all given in percent. Each regression also uses the lagged sentiment score of day −1 interacted with firm size terciles as the independent variables of interest. The first row shows the lagged sentiment variable, the second and third rows show this sentiment score interacted with the two binary variables Size medium and Size large, which are equal to one if the firm is in the middle and upper market value tercile, respectively. All sentiment variables are standardized to have a zero mean and variance of one. SA % short articles is the percentage of articles classified as "short" from all articles published for a specific firm on a specific day and missing if no articles exist. SA % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no articles exist. ST % bear tweets is the percentage of tweets classified as "bearish" from all self-disclosed tweets for a specific firm on a specific day and missing if no self-disclosed articles exist. ST % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no tweets exist. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. RP mean ESS (inverted) corresponds to the mean inverted Event Sentiment Score of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. t-Statistics are shown in parentheses, standard errors are clustered by firm and year-month. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	Volume	Volume	Volume	Volume	Volume	Volume	Volume
$Volume_{-1}$	0.658***	0.657***	0.658***	0.658***	0.658***	0.665***	0.588***
	(48.550)	(88.518)	(48.388)	(48.399)	(90.415)	(103.840)	(53.511)
Ln(Market cap)	−56.226***	−98.319***	−56.164***	−56.288***	−97.798***	−62.355***	−36.125***
	(−5.324)	(−13.578)	(−5.301)	(−5.310)	(−13.545)	(−15.223)	(−11.501)
Book-to-market	3.203	6.631**	3.194	3.283	6.590**	3.316*	1.306
	(0.719)	(2.124)	(0.717)	(0.740)	(2.122)	(1.852)	(0.314)
Return on assets	−0.930**	−0.630***	−0.930**	−0.934**	−0.630***	−0.539***	−0.658***
	(−2.185)	(−3.286)	(−2.184)	(−2.201)	(−3.279)	(−4.233)	(−4.237)
BHAR	0.437***	0.371***	0.437***	0.431***	0.370***	0.268***	0.155***
	(3.962)	(5.163)	(3.956)	(3.859)	(5.127)	(5.540)	(5.321)
Id. volatility	35.253***	26.283***	35.309***	35.280***	26.384***	23.969***	22.668***
	(5.184)	(8.147)	(5.124)	(5.159)	(8.180)	(10.242)	(9.464)
	SA agreement	ST agreement	SA % short articles	SA % neg. words	ST % bear tweets	ST % neg. words	RP ESS inverted
$Sent. variable_{-1}$	−2.743	−8.865***	−0.763	−4.331	−9.833***	0.683	1.149*
	(−0.353)	(−2.692)	(−0.265)	(−1.053)	(−4.244)	(1.165)	(1.943)
* Size medium	3.208	18.823***	0.386	4.075	5.871**	−0.648	−0.570
	(0.405)	(5.075)	(0.130)	(0.954)	(2.448)	(−0.946)	(−0.997)
* Size large	2.118	8.440**	1.321	4.120	10.463***	−0.430	−0.682
	(0.269)	(2.485)	(0.401)	(0.980)	(4.581)	(−0.700)	(−1.187)
Constant	850.291***	1,386.357***	849.138***	850.975***	1,377.567***	871.676***	509.230***
	(4.910)	(13.177)	(4.882)	(4.894)	(13.138)	(14.510)	(10.707)
Observations	67,406	755,427	67,406	67,406	755,427	2,321,144	1,563,067
R-squared	0.804	0.751	0.804	0.804	0.751	0.736	0.712
Firms	3,677	4,825	3,677	3,677	4,825	5,289	4.125
Year-month FE	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes

small stocks the relationship of ST agreement and trading volume is highly negative, with a one standard deviation decrease in agreement increasing the trading volume by nearly nine times the stock's market capitalization. This is at odds with the findings of Antweiler and Frank, 2004 who find an effect in this direction intraday, but in the different direction for the following day. A traditional hypothesis is that disagreement among investors induces trading, in line with our results. Tetlock, 2007 however also argue that agreement on a

Table 4.13: Investor Sentiment and Bid-Ask Spreads.
This table shows the results of regressions on the trading volume on day 0 on a firm-day basis. The independent variable Bid-ask spread is the difference of the highest bid price and the lowest ask price relative to the ask price at the daily closing time. The independent control variables include the Bid-ask spread on day −1, Ln(Market value) is the natural logarithm of a firm's market value in thousand US-$, Book-to-market is the ratio of a firm's book and market value, and Return on assets is a firm's yearly net income divided by its total assets. The Buy and hold abnormal return (BHAR) is the cumulated abnormal return calculated with the Fama French Five Factor Model over the preceding 252 trading days and the Idiosyncratic volatility is the abnormal return's standard deviation over the preceding 252 trading days. Volume, Return on assets, Buy and hold abnormal return, and Idiosyncratic volatility are all given in percent. Each regression also uses the lagged sentiment score of day −1 interacted with firm size terciles the independent variables of interest. The first row shows the lagged sentiment variable, the second and third rows show this sentiment score interacted with the two binary variables Size medium and Size large, which are equal to one if the firm is in the middle and upper market value tercile, respectively. All sentiment variables are standardized to have a zero mean and variance of one. SA % short articles is the percentage of articles classified as "short" from all articles published for a specific firm on a specific day and missing if no articles exist. SA % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no articles exist. ST % bear tweets is the percentage of tweets classified as "bearish" from all self-disclosed tweets for a specific firm on a specific day and missing if no self-disclosed articles exist. ST % negative words is the percentage of negative words from all words published for a specific firm on a specific day and missing if no tweets exist. The classification of negative words in SA articles and ST tweets is based on those words that match in the Loughran and McDonald, 2011 dictionary. RP mean ESS (inverted) corresponds to the mean inverted Event Sentiment Score of all RavenPack News Stories for a specific firm on a specific day with a relevance of 90 and higher. The score is inverted by 100 minus the original ESS. t-Statistics are shown in parentheses, standard errors are clustered by firm and year-month. *, **, and *** denote statistical significance at the 10, 5, and 1% level.

	Bid-ask spread	Bid-ask spread	Bid-ask spread	Bid-ask spread	Bid-ask spread	Bid-ask spread	Bid-ask spread
Bid-ask spread$_{-1}$	0.514***	0.379***	0.514***	0.514***	0.380***	0.418***	0.465***
	(7.845)	(26.973)	(7.840)	(7.838)	(27.155)	(39.644)	(23.446)
Ln(Market cap)	−0.049***	−0.121***	−0.049***	−0.049***	−0.121***	−0.130***	−0.087***
	(−5.281)	(−14.423)	(−5.270)	(−5.275)	(−14.471)	(−19.915)	(−13.544)
Book-to-market	0.002	0.004	0.002	0.002	0.004	0.004**	0.017**
	(0.886)	(1.290)	(0.881)	(0.866)	(1.299)	(2.159)	(2.551)
Return on assets	0.000*	−0.001***	0.000*	0.000*	−0.001***	−0.001***	0.000**
	(−1.782)	(−3.643)	(−1.790)	(−1.765)	(−3.591)	(−5.396)	(−2.379)
BHAR	0.000***	−0.001***	0.000***	0.000***	−0.001***	−0.001***	−0.001***
	(−4.006)	(−16.495)	(−4.005)	(−4.013)	(−16.373)	(−18.675)	(−12.201)
Id. volatility	−0.003	−0.021***	−0.003	−0.003	−0.021***	−0.022***	−0.003
	(−1.383)	(−5.738)	(−1.334)	(−1.381)	(−5.915)	(−6.646)	(−0.648)
	SA agreement	ST agreement	SA % short articles	SA % neg. words	ST % bear tweets	ST % neg. words	RP ESS inverted
Sent. variable$_{-1}$	−0.004	0.022***	−0.002	0.003	0.012***	−0.002	0.001
	(−0.939)	(6.348)	(−0.821)	(0.783)	(2.741)	(−0.992)	(0.966)
* Size medium	0.004	−0.022***	0.002	−0.003	−0.012***	0.000	−0.002
	(0.972)	(−6.036)	(0.739)	(−0.821)	(−2.650)	(0.173)	(−1.125)
* Size large	0.003	−0.020***	0.003	−0.003	−0.014***	0.001	−0.002
	(0.822)	(−5.665)	(0.858)	(−1.040)	(−3.127)	(0.580)	(−1.135)
Constant	0.847***	1.966***	0.846***	0.845***	1.973***	2.056***	1.367***
	(5.551)	(15.749)	(5.539)	(5.544)	(15.818)	(21.079)	(13.893)
Observations	67,406	755,426	67,406	67,406	755,426	2,321,142	1,563,063
R-squared	0.710	0.586	0.710	0.710	0.586	0.608	0.612
Firms	3,677	4,825	3,677	3,677	4,825	5,289	4,125
Year-month FE	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes

social media platform can induce trading if this is mainly derived from noise traders. This agreement among noise traders then in turn creates disagreement between noise traders and rational traders, inducing trading between both investor groups. It becomes clear that due to the fact that we observe the interaction of a subgroup of investors on social media, there is no obvious effect direction to be expected from investor agreement beforehand. Applying the reasoning of Tetlock, 2007 the estimated negative relationship between agreement and trading volume indicates that the sentiment of both trading parties is represented on ST. No conclusion can, however, be drawn to whether this is disagreement among noise traders or between noise and rational traders. Interestingly, the effect is only negative and economically significant for small size stocks. The two possible reasons we previously gave for the size dependence of the sentiment effect was the asymmetry of information around smaller stocks which makes them harder to value, and that small stocks have higher individual investor ownerships. If our sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks better. In this context the same logic applies, as this informational asymmetry or higher shares of individual ownersthips may foster disagreement and thereby induce trading. For large size stock the effects gets close to zero. For medium sized stocks, however, the effect clearly and economically significantly changes the direction from -8.865 to $+9.958$.

For the self-disclosed ST sentiment measure we see a significant negative sign for volume and a positive sign for bid-ask spreads. This shows that positive sentiment increases stock liquidity, i. e., increases trading volume and decreases bid-ask spreads. Tetlock, 2007 find that negative sentiment predicts increases in trading volume and explain it through disagreement between pessimistic noise traders on social media and rational traders. We find a relationship in the other direction, but Tetlock, 2007's explanation works both ways. In our case it means that disagreement between bullish noise traders on ST and rational traders drives trading volume. In combination with the volume inducing effect of ST disagreement, this could in fact tentatively indicate that noise traders play an important role on ST. These noise traders induce stock volume as they trade stocks among each other and with rational traders but do not affect stock returns, as this effect is arbitraged away by rational investors. Remarkably, this is only the case for small stocks. For medium and large stocks this effect becomes considerably smaller and quite close to zero. Clearly, company size has again to be part of the explanation and the possible reasons are analogous to the size dependence of the agreement measure discussed earlier.

What is particularly remarkable is that we see two distinctly separate effects of self-disclosed sentiment for SA and ST. While SA sentiment predicts stock returns and no stock liquidity, for ST it is precisely the other way around. This brings out two key results of this examination. Firstly, self-disclosed sentiment seems to be a very valuable information which in our study vastly outperforms sentiment tone measures, both for SA and ST. Secondly, our quality driven source is thereby more connected to stock returns, while our quantity driven source more to stock liquidity.

4.7 Conclusion

Our main first result is that negative self-disclosed sentiment from SA produces large negative returns the next day. The average daily difference of returns from a positive sentiment portfolio over a negative sentiment portfolio is 0.40%. ST and RP as well as sentiment tone from SA also produce statistically significant return predictions which are, however, economically small and vastly under-perform the predictive power of SA self-disclosed sentiment. There are three possible explanations why this sentiment effect arises. First, in the case that prices are moved by rational traders, SA contains new price-relevant information before it is factored into the stock price, while ST and RP do not. Second, in the case that prices are moved by noise traders, SA, ST, and RP may be used by separate groups of investors and only the irrational sentiment of SA users is representative of a group of investors with enough market power that actually moves stock prices. Third, the out-performance of SA self-disclosed sentiment may also arise because the means of measurement, i. e., self-disclosure, works considerably better for SA than it does for ST. This explanation is possible assuming both, rational traders or noise traders. Although it is hard to differentiate between the possible reasons, the persistence of our sentiment effect, i. e., the lack of a return reversal, indicates price-relevant informational content in SA self-disclosed sentiment. For ST self-disclosed sentiment, on the other hand, a return reversal indicates noise or misvaluation characteristics. This suggests that irrational sentiments led to misvaluations on StockTwits and indicates a fundamental difference between the two social media platforms. Furthermore, we find evidence that self-disclosed sentiment from ST in fact measures investor sentiment, as shown by our second main result.

Our second main result is that self-disclosed disagreement and positive self-disclosed sentiment from ST induce trading volume the next day, while SA and RP, as well as ST sentiment tone do not. This shows that self-disclosure as the means of measurement does in fact measure relevant investor sentiments on ST. These sentiments are, however, related to trading activity and not to stock returns. A reason for this could be that this activity is generated by noise traders who trade among themselves or with rational traders. The lack of a significant stock movement then indicates that no rational trading takes place, i. e., no new information are processed. It seems that for trading activity the quantity oriented nature of ST delivers a much better indication and that the quality oriented nature of SA delivers a much better indication of stock returns. The fact that disagreement as well as positive sentiment on ST induce trading volume could tentatively indicate that noise traders play an important role on ST. The argument is that if investors agree on ST they have to trade with different investors with whom they disagree. Consequently, disagreement between bullish noise traders on ST and rational traders drives trading volume.

Our third main result is that the sentiment effect on returns as well as the effect on trading volume are predominantly driven by small stocks. The average daily difference of returns from a positive self-disclosed SA sentiment portfolio over a negative sentiment increases to 0.88% for firms below the first size tercile. For small stocks a one standard deviation increase in self-disclosed ST disagreement increases the trading volume by nearly nine times the stock's market capitalization and a one standard deviation decrease in our self-disclosed ST sentiment measure (more positive sentiment) increases the trading volume by nearly ten times the stock's market capitalization. One reason for the fact that the sentiment effect is so concentrated among small stocks maybe that the distribution of information about small stocks is more inefficient. In an inefficient and asymmetric informational context investor sentiment plays a more important role. For rational investors this means that price-relevant information may diffuse more slowly thereby causing a lagged reaction. For an irrational investor the fewer information about a firm is available the more is left to the investor's imagination. Another explanation for the size dependence of the sentiment effect is that small stocks have higher individual investor ownerships. If our sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks better.

Chapter 5
Conclusion

With respect to this dissertation's first subject area on the influence of the settlement of law enforcement activities on corporate valuation, two analyses are carried out. The first one considers corporate prosecution agreements in the US across all industries and their impact on shareholder wealth. The second analysis focusses on all legal actions against the 25 largest global financial institutions and goes beyond the first analysis in multiple ways. Although both investigations are different from each other in terms of defendant industry, legal action types, as well as the investigated effects, some common rèsumè can be drawn.

The settlement of lawsuits is generally viewed as a positive event by capital market participants in both papers. At the time of the settlement, negative information has already been priced in. The actual settlement then resolves the uncertainty with respect to the expected outcome thereby increasing the defendants stock market valuation. The settlement amount is of differing influence in both investigations. In the financial industry a very strong relationship is found that larger monetary settlements lead to more pronounced equity market reactions on the announcement day of the settlement. The explanation is that uncertainty reduction is the main reason for this positive effect and that higher monetary settlement amounts are associated with greater reductions of uncertainty. For the settlement of corporate criminal prosecution agreements, the empirical evidence is somewhat different. On the settlement day there is no significant relationship between the the size of the settlement and the shareholder wealth effect. For a longer time period around the settlement day the relationship even becomes negative, indicating that larger settlement amounts lead to more negative stock market reactions. The reasons for these differing results can likely be attributed to the different scopes of investigation. For criminal prosecution agreements the size of the settlement seems to be less important than for civil settlements, as for these settlements other characteristics than the monetary penalty are more relevant. For severe misconducts regularly civil as well as criminal legal actions are taken. The subsequent settlement amounts are typically considerably larger for the civil settlements than for the criminal ones. A recent example of this is the emissions scandal of Volkswagen. Civil charges have been resolved in June 2016 with a payment of 15.3 billion US dollars while criminal charges were only settled later in April 2017 with the payment of a 2.8 billion US dollars fine. Although the criminal penalty is still sizeable it is distinctly smaller than the civil penalty. Criminal agreements, however, often entail considerable non-monetary requirements. Furthermore, with a criminal agreement further potential catastrophic consequences are avoided, like debarment, loss of licences, or loss of government contracts. These consequences, although non-monetary in nature, could cause considerable costs for corporations. Their avoidance is consequently another major source of uncertainty resolution that is not measured by the monetary penalty.

One main result of the first paper is that the use of pretrial diversions does not appear to be more beneficial to firms than the use of PAs. On the contrary, the announcement of settlements through DPAs or NPAs leads to significantly lower share price reactions than the announcement of settlements through PAs, suggesting that shareholders favor PAs over pretrial diversions. Therefore, the argument that particularly large corporations are treated preferentially and suffer comparatively less when using pretrial diversions cannot be confirmed by the empirical results, at least from a shareholder's perspective. The likelihood of a certain agreement type is strongly dependent on the crime committed and corporate governance seems to be of importance as poorer board-related governance structures are associated with an increased likelihood of a criminal conviction through a PA.

The second paper focusses on the financial industry and goes beyond the first paper in several ways. To provide a holistic overview of the impact of financial penalties on banks, the impact on stock, bond, and CDS markets is analyzed, the speed of information processing in these markets, potential spillovers to comparable financial institutions, effects on banks' systemic risk, as well as on a bank's cash flow, net income, and lending. Given that the banking sector plays central role to the economy, it is of particular importance to gain a first understanding of the effect of legal proceedings and their subsequent settlements on a banks default risk as well as potential systemic spillover effects.

Beyond to the aforementioned general positive shareholder wealth effect as well as this effect's strong positive dependence on the size of the settlement, it is found that the perceived default risk is lower as shown by lower bond yields and tighter CDS spreads. The results further indicate that stock and CDS markets directly react to the resolution of enforcement actions and then transmit the effect to the bond market which reacts indirectly with a lag of one day. The impacts of legal settlements is not confined to the bank receiving the penalty. It is found that the resolution of legal proceedings leads to positive valuation effects for comparable financial institutions with pending lawsuits with the same regulator or law enforcement entity. These results suggest that the unraveling of bank fines appears to be associated with positive spillovers. On the one hand this underscores the systemic importance of legal proceedings against banks, on the other hand this should also alleviate concerns with regard to the settlements' systemic impact. At the same time, employing three different measures for the sued bank's contribution to systemic risk, a weak evidence is found for an increase of that bank's contribution to systemic risk in the size of the relative monetary penalty. This mixed evidence underscores the systemic relevance of law enforcement actions against banks, as pointed out by the European supervisory authorities (European Systemic Risk Board, 2015).

Finally, monetary penalties reduce a bank's annual cash flow nearly one-to-one in the year they are announced, reflecting the cash flow-effectiveness of these settlements. In the year of the resolution announcement, however, the bank's net income is unaffected by the announced penalties. This provides tentative evidence that banks on average correctly anticipate the impending financial penalties in previous financial years and substantiates the notion that the positive valuation effects by stock, bond, and CDS market participants are driven by the resolution of uncertainty.

In the second subject area of this dissertation the influence of sentiment derived from social media on the stock market is investigated. To this end two major social media sources are considered, Seeking Alpha, which contains articles classified into buy/sell categories by the author, and StockTwits, which contains shorter messages also tagged with author-disclosed sentiment. These social media sources are further compared with more traditional news media using the RavenPack database.

The first main result is that negative self-disclosed sentiment from the Seeking Alpha social media platform produces large negative returns the next day. The average daily difference of returns from a positive sentiment portfolio over a negative sentiment portfolio is 0.40%. The other social media platform StockTwits and RavenPack as measure of traditional news media tone, as well as media tone from Seeking Alpha also produce statistically significant return predictions which are, however, economically small and vastly under-perform the predictive power of Seeking Alpha self-disclosed sentiment. There are three possible explanations why this sentiment effect arises. First, in the case that prices are moved by rational traders, Seeking Alpha contains new price-relevant information before it is factored into the stock price, while StockTwits and RavenPack do not. Second, in the case that prices are moved by noise traders, Seeking Alpha, StockTwits, and RavenPack may be used by separate groups of investors and only the irrational sentiment of Seeking Alpha users is representative of a group of investors with enough market power that actually moves stock prices. Third, the out-performance of Seeking Alpha self-disclosed sentiment may also arise because the means of measurement, i. e., self-disclosure, works considerably better for Seeking Alpha than it does for StockTwits. This explanation is possible assuming both, rational traders or noise traders. Although it is hard to differentiate between the possible reasons, the persistence of the sentiment effect, i. e., the lack of a return reversal, indicates price-relevant informational content in Seeking Alpha self-disclosed sentiment. Furthermore, evidence is found that self-disclosed sentiment from StockTwits in fact measures investor sentiment, as shown by the second main result.

The second main result is that self-disclosed disagreement and positive self-disclosed sentiment from StockTwits induce trading volume the next day, while Seeking Alpha and RavenPack, as well as StockTwits sentiment tone do not. This shows that self-disclosure as the means of measurement does in fact measure relevant investor sentiments on StockTwits. These sentiments are, however, related to trading activity and not to stock returns. A reason for this could be that this activity is generated by noise traders who trade among themselves or with rational traders. The lack of a significant stock movement then indicates that no rational trading takes place, i. e., no new information are processed. It seems that for trading activity the quantity oriented nature of StockTwits delivers a much better indication and that the quality oriented nature of Seeking Alpha delivers a much better indication of stock returns. The fact that disagreement as well as positive sentiment on StockTwits induce trading volume could tentatively indicate that noise traders play an important role on StockTwits. The argument is that if investors agree on StockTwits they have to trade with different investors with whom they disagree. Consequently, disagreement between bullish noise traders on StockTwits and rational traders drives trading volume.

The third main result is that the sentiment effect on returns as well as the effect on trading volume are predominantly driven by small stocks. The average daily difference of returns from a positive self-disclosed Seeking Alpha sentiment portfolio over a negative sentiment increases to 0.88% for firms below the first size tercile. For small stocks a one standard deviation increase in self-disclosed StockTwits disagreement increases the trading volume by nearly nine times the stock's market capitalization and a one standard deviation decrease in the self-disclosed StockTwits sentiment measure (more positive sentiment) increases the trading volume by nearly ten times the stock's market capitalization. One reason for the fact that the sentiment effect is so concentrated among small stocks maybe that the distribution of information about small stocks is more inefficient. In an inefficient and asymmetric informational context investor sentiment plays a more important role. For rational investors this means that price-relevant information may diffuse more slowly thereby causing a lagged reaction. For an irrational investor the fewer information about a firm is available the more is left to the investor's imagination which then makes her more sensitive to sentiment. Another explanation for the size dependence of the sentiment effect is that small stocks have higher individual investor ownerships. If the employed sentiment measures proxy the sentiment of individual investors, then it should consequently predict the returns on small stocks better.

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I declare upon my word of honor that the doctoral thesis submitted herewith is my own work. All sources and aids used have been listed. All references or quotations in any form and their usage have been clarified.

The dissertation has not been submitted for examination purposes to any institution before.