Agreeing to Disagree: Informativeness of Sentiments in Internet Message Boards

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Abstract

We study the informativeness of sentiments in posts on HotCopper, the largest online stock message board in Australia. We find that positive sentiment is associated with noise induced (uniformed) trading whereas negative sentiment contains value-relevant information about a firm's performance. Our empirical findings suggest that short selling activity reduces overreactions of abnormal returns in a noisy environment on the same day. Furthermore, we observe that low levels of sentiment homogeneity relate to significantly lower annual earnings surprise. This supports the view that disagreements amongst sentiments are a signal of bad news about firm fundamentals. Lastly, we decompose our message board sentiment index and reveal that it is predominantly explained by the macroeconomic fundamental component rather than the behavioural component.

Keywords: Financial innovation; Internet message boards; Sentiments; Agreements; Volatility

JEL classification: G7, G14

Declarations of interest: none

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1. Introduction

In the past decade, the growth in the use of online technologies such as social media platforms to disseminate the interpretation of financial news meant that investors face a more disaggregated set of informational channels than ever before. We investigate how this form of financial innovation may add value-relevant information and how it relates to risks in stock price returns. We employ the sentiments of posts on HotCopper, the largest Australian online stock message board, to find that negative sentiment contains value-relevant information about a firm's performance and that disagreements amongst sentiments are a signal of bad news about firm fundamentals. Further, we reveal that volatilities of stock price returns induces higher levels of posting activities.

Based on the seminal work of Antweiler and Frank (2004), studies on social media outlets (e.g.; internet message boards, Twitter[1], Google[2]) examine how sentiment, message- and internet search volume are related to reactions in the equities markets. Studies on internet message boards have been contentious surrounding the return predictability of sentiment shared on social media (Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das and Chen, 2007; Kim and Kim, 2014). Chen et al. (2014), however, find in their study that the fraction of negative words of articles and comments published on the peer-based advising platform Seeking Alpha predicts returns over different time horizons. The difference in results to other studies are mainly explained by the broader sample and the more sophisticated design of messages posted on Seeking Alpha. Nonetheless, the results only relate to negative sentiment and the relation between positive sentiment and equities market activity has received little attention, even though it is equally or even more so for internet message boards.[3]

[1]The social media phenomena Twitter is rather found to be an echo of equities market activity (Sprenger et al., 2014) despite its indisputable US influence in political discussions. Recent studies relate emotions and moods on Twitter with equities market activity (Bollen et al., 2011; Zhang et al., 2011; Nofer and Hinz, 2015). However, results are ambiguous. Nofer and Hinz (2015) for example argue that follower-weighted social mood levels would predict market returns on the subsequent day. Bollen et al. (2011) only find significant relations for the mood "calm" with regards to market performance. Sprenger et al. (2014) on the other hand applied the method used by Antweiler and Frank (2004) on Twitter and found that individual stock market activity impacts on tweet activity rather than the other way around.

[2]A number of studies examine the relation between the Google Search Volume Index (SVI) and market activity to understand the role of sentiment and social media activity in terms of price discovery and investor attention. Google related studies on the other hand analyze the implications of Google search volume. They derive market sentiments on the aggregate level and suggest that Google search volume predicts market developments (Da et al., 2011; Da et al., 2015). Da et al. (2011) find that search frequency in Google (SVI) is a direct measure of retail investor attention and that SVI predicts higher stock prices the subsequent two weeks with potential return reversals within one year. Drake et al. (2012) show that investor information demand increases market efficiency surrounding earnings announcements. Other studies relate SVI with market indices and volatility (Vlastakis and Markellos, 2012; Vozlyublennaia, 2014; Andrei and Hasler, 2015; Da et al., 2015). As suggested by Tetlock (2007), negative terms in English language are more reliable for identifying investors sentiment. Consequently, Da et al. (2015) only applied negative terms to form their SVI based FEARS index used to measure the household sentiment. They find that the FEARS index predicts market returns, revealing contemporaneous low returns but higher returns the subsequent day. This might be consistent with the noise trading theory and the sentiment-induced divergence of asset pricing from the fundamental values.

[3] Antweiler and Frank (2004) and Leung and Ton (2015) show that sentiment expressed on internet message boards are strongly biased towards positive sentiment.

Tumarkin and Whitelaw (2001) find a contemporaneous relation between message board activity and returns. Antweiler and Frank (2004) find significant, but negative contemporaneous correlation between stock returns and the message volume the following day. Das and Chen (2007) find no significant relationship between internet message board sentiment and individual stock prices. However, at the aggregate level, results indicate a relation between sentiment and stock prices. In another study, Kim and Kim (2014) compare self-disclosed and machine classified sentiment based on the Naïve Bayes algorithm and find little evidence that sentiment would predict future stock returns at an individual or aggregate level (also for market volatility and trading volume). Chen et al. (2014) show in their study that opinions on Seeking Alpha strongly predict future returns and earnings surprises. Similar to other media related studies, they find no significant relation for positive word categories and therefore focused on the relation of the negativity of articles and comments with future stock performances. Leung and Ton (2015) find that message board activity strongly relates to small market capitalization activity. We argue that bullish stock portfolios outperform bearish stocks in the same month, however with diminishing differences in subsequent months. Lead-lag-regressions show predictive power of message volume and sentiment for the next two days for small stocks however only with little economic significance. Renault (2017) provides evidence that the previous day last half-hour change in investor sentiment helps to forecast intraday stock index returns. In this study, we further attempt to analyze the role of stock message boards in the price discovery process. We examine whether positive and negative sentiment convey different levels of value relevant market information and further elaborate on implications for financial regulators.

A common term used in relation with investor sentiment and noise trading is the term 'Bullishness'. Brown and Cliff (2004) define 'Bullishness' as investor sentiment attached to some degree of outperformance of stocks, generally measured by their positive abnormal returns. However, classical finance theory does not support the role of investor sentiment. It argues that mispricing will be offset by rational investors who statistically optimize their portfolio, leading to a price equilibrium based on arbitrage. A deviation of market pricing and a firm's fundamental would therefore result from an uninformed demand shock and limits on arbitrage (Baker and Wurgler, 2006). De Long et al. (1990) argue that if irrational noise traders would trade based on their erroneous stochastic beliefs they would affect prices and create risk in the asset pricing. As a result, excess market volatility, divergence from fundamental values and the reversion of stock returns are surrounded by market activity induced by noise traders. According to this theory, when sentiment rises, uninformed traders increase their capital allocation to assets with higher risk classes and will drive prices away from their fundamental. This is followed by returns reversal and a convergence to the price equilibrium (Kim and Kim, 2014). If returns do not reverse hereafter, it implies that sentiment convey value relevant information for market participants.

Our study differentiates itself from former studies on internet message boards. We examine the relation between distinctive sentiment environments (positive and negative) and equities market activity. Former studies mainly focused on the influence of average bullishness scores or only negative sentiments on social media. However, we show that the segmentation of sentiment is essential in sentiment analysis with significantly distinctive implications for equities markets (uninformed vs. informed trading). Using the sentiment disclosed by posters on HotCopper, we do not rely on machine learning algorithms compared to former studies (Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004; Das and Chen, 2007). For example, Das and Chen (2007) find that the popular Naïve Bayes Algorithm, revealed only a 50% accuracy on sentiment classification for their study. Our sample is therefore free from classification bias.

Second, from best of our knowledge this is the first study to shed light on the relationship between short selling activity and sentiment expressed on internet message boards. Former studies have argued that limits on arbitrage resulting from short time horizons and higher cost/risk profiles of especially low capitalization and growth stocks, might prevent contrarian arbitrageurs to trade against noise traders (De Long et al., 1990; Shleifer and Vishny, 1997; Baker and Wurgler, 2007). Short selling, as one mean of arbitrage, is regulated by the Corporations Act 2001 and the Corporations Regulations 2001 in Australia[4]. Most short selling activity in Australia is based on covered short sales, since naked short sales are generally restricted except given circumstances. A violation of reporting would result in an offence as defined by the Australian Securities & Investments Commission (ASIC). In our study, we use the short selling position data set from the ASIC to examine whether short selling activity contributes to the price stabilization process in a noisy or uninformed trading environment.

Third, we analyze a broad data sample of 3,050 stocks with 4,586,271 stock forum messages between January 2008 and May 2016. Previous studies usually focused on tech companies or on the most active firms on the internet message board of up to 100 stocks for an only short period of time (usually less than one year). Our broad sample therefore allows us to examine the distinctive relationship between social media and equities markets on the aggregate and individual stock level over a longer time horizon. Due to their focus at the aggregate index level, former studies were thus prone to cancelation errors of overly optimistic or pessimistic individual stock sentiments on the aggregate level (Kim and Kim, 2014) and they were also subject to time effects.

[4] For more information please visit http://asic.gov.au/regulatory-resources/find-a-document/regulatory-guides/rg-196-short-selling/.

Fourth, we examine the relation between sentiment homogeneity and firm's fundamentals around annual earnings announcements as well as equities market performance. As previous studies only examined how agreement on sentiment (namely the standard deviation of posted sentiments) relates to future stock returns and volatility, we furthermore analyze how sentiment homogeneity cross-sectionally and contemporaneously relates to activities in the equities market.

We show that positive sentiment shared on internet message boards induce noisy (uninformed) market trading activities with significant contemporaneous abnormal returns but negative return reversals the following days. We find empirical evidence that short selling activity reduces overreactions on positive sentiment expressed on internet message boards on the same day. Due to costly short selling activities for especially low capitalization and growth stocks, we argue that only informed short sellers would take the risk to bet against positive sentiment traders. Furthermore, we find that stocks with negative sentiment postings experience significantly lower abnormal returns. These effects are made visible by the segmentation of an average sentiment score into positive or negative sentiment scores. The results hold for small capitalization stocks. Additionally, we show that stock price volatility and internet message posting volume correlate with each other, however with stronger impact from volatility to posting volume. For the aforementioned implications on sentiment and stock price volatility we find that significance and magnitudes in results also strongly depend on the differentiated analysis on aggregate index or individual stock level.

Finally, we observe an agreement convergence pattern prior to annual earnings announcements and we show that stocks with low levels of sentiment homogeneity (low sentiment and/or agreement) experience significantly lower annual earnings surprise. This supports the view that disagreement and/or low sentiment levels amongst investors are a signal of bad news about firm fundamentals. The overall findings suggest that positive and negative sentiment are drivers for noise- and value-prompted price movements, respectively. Also, we show that the level of sentiment homogeneity is an indicator on changes on firm's fundamentals before annual earnings announcements.

In section 2 we describe the message board data and financial data. Section 3 shows the event study results. Section 4 encompasses the main regression analysis and results from vector auto regressions as well as granger causality tests. Section 5 describes the cross-sectional portfolio performance based on sentiment and agreement as well as results from regressions regarding earnings surprises. Section 6 concludes the overall findings.

2. Data and research design

The data for this study was captured from the HotCopper Message Board, which is Australia's largest message board with more than 250,000 registered members, and more than 200,000 unique website visitors every month. Most members of this internet message board are Australian investors and share market traders generating more than 21 million monthly page views. In Australia, HotCopper has 18 times the traffic compared to its nearest competitors and comparable financial websites. HotCopper is a free access forum and enables investors to discuss on financial topics such as the ASX (Australian Securities Exchange) and foreign stock markets, IPOs or Foreign Currency Trading.[5] Our data set contains 4,586,271 forum messages posted in the period from January 2008 to May 2016. We include examples of opinions and messages extracted from HotCopper in Table 1 to provide a sense of information depth and content of board messages. Figure 1 compares the posting activity for small and large stocks of our current data set with our previous study (Leung and Ton, 2015). Small stocks still account for most of posting activity with similar pattern compared to the past study. Peaks of message board activity have moved to the opening (10 a.m.) trading hours of the ASX.

<INSERT FIGURE 1 ABOUT HERE>

2.1. Stock message board sentiment and agreement

Previous studies were compelled to apply text classifier for sentiment classification of individual board messages, since board users did not directly reveal their recommendations (Buy vs. Sell) on internet message boards. Outcomes therefore relied on quality and the accuracy of the applied methods. Our study has the advantage to fall back on board messages with self-disclosed sentiment and therefore lowers the risk of false sentiment classification. HotCopper allows its users to classify their sentiment along 7 categories: "Hold", "Short-term Buy", "Long-term Buy", "Buy", "Short-term Sell", "Long-term Sell" and "Sell". As time effects are difficult to measure (e.g., long-term sell vs. sell), we assign all short-term, long-term and sell/buy recommendations to "Sell/Buy". Different findings on the relation of internet board message sentiment and market activity are existent and may be attributed to different measures of sentiment. In this connection Baker and Wurgler (2007) conclude that one of the key issues for researchers to address is the matter of sentiment measurement and the quantification of its impact.

Some authors find contemporaneous correlations between sentiment and stock returns (Antweiler and Frank, 2004), others show that only negative sentiment predicts future stock returns

[5] For more information please visit https://hotcopper.com.au/about/.

(Chen et al., 2014). In turn, Kim and Kim (2014) argue that stock returns rather condition sentiment reaction than the other way around. All studies have in common, that analysis was either based on average sentiment scores or only contemplated the impact of negative sentiment on the capital market. To examine whether sentiment partitioning may improve the predictive power of message board sentiment scores, we employ the standardized Bullishness index from Antweiler and Frank (2004) for our sentiment analysis and disentangle the average sentiment index into a segmented positive and negative sentiment score. Only buy and sell messages (forth on called financially relevant messages) are included into the bullishness index. The total number of relevant messages is therefore defined as $M_{i,t} = M_{i,t}^{BUY} + M_{i,t}^{SELL}$.

The standardized bullish index $Bullishness_{i,t}$ for stock i at time t is defined as:

$$Bullishness_{i,t} \equiv \frac{M_{i,t}^{BUY} - M_{i,t}^{SELL}}{M_{i,t}} \cdot \ln(1 + M_{i,t}) \quad (1)$$

To measure the differentiated impact of positive and negative sentiment, we define the positive and negative sentiment for stock i on day t as:

$$PosSentiment_{i,t} \equiv \ln(1 + M_{i,t}^{BUY}) \quad (2)$$

and

$$NegSentiment_{i,t} \equiv \ln(1 + M_{i,t}^{SELL}) \quad (3)$$

We additionally include the agreement index $A_{i,t}$ (see Antweiler and Frank, 2004) to measure the degree of agreement between sentiments of posted messages. This score is then used to examine how sentiment and agreement jointly (we define it as sentiment homogeneity) convey fundamental information around annual earnings announcements.

The agreement index $A_{i,t}$ is defined by:

$$Agreement_{i,t} \equiv 1 - \sqrt{1 - \left(\frac{M_{i,t}^{BUY} - M_{i,t}^{SELL}}{M_{i,t}}\right)} \quad (4)$$

<INSERT TABLE 1 ABOUT HERE>

2.2. Financial Data

We obtain individual daily trading data from Compustat and Securities Industry Research Centre of Asia-Pacific (SIRCA) for our observation period of January 1st, 2008, to May 31st, 2016. The data contains exchange ticker code for each transaction with timestamp, price, price returns, highest and lowest daily price. We calculate $Volatility_{i,t-30,t-1}$ as the 30 trading-day standard deviation of returns prior to day *t*. Following Chakrabarty et al. (2012), we define daily volatility, $Volatility_{i,t}$, as the relative difference between the highest and the lowest price of the stock *i* on day *t* scaled by the daily closing price. We use the value-weighted All Ordinaries Index to proxy the market performance, since it includes 500 constituents and is therefore the broadest index in the Australian market. Using the market index, we calculate abnormal returns, $AbRet_{i,t-j,t-k}$, as the difference between the firm's compounded stock return and value-weighted market return over a defined holding period j to k (see Akbas, 2016). We obtain data on analyst recommendations and earnings forecast from the IBES summary, surprise and detail history file in order to examine the value relevant information content of board messages around financially relevant company events, in this case annual earnings announcements. The IBES summary file contains information about the number of recommendation upgrades/downgrades for firm *i* on day *t* ($Upgrade_{i,t}/Downgrade_{i,t}$). The IBES surprise history file tracks the mean consensus Earnings per Share-estimate for a particular fiscal period. We use this metric to assign positive and negative mean earnings surprise dummy variables to firm *i* on day *t*, ($PosMeanES_{i,t}/NegMeanES_{i,t}$). We also constructed median consensus analyst forecast to calculate annual earnings surprises for our analyses. The approach will be detailed in a later section. Furthermore, we download short sell position data from the Australian Securities & Investment Commission (ASIC) available between June 2010 and May 2016 which includes information about a firm's reported short position and the share of reported short positions from total shares outstanding. This data is used to evaluate the impact of short-selling on sentiment related trading activities in later sections.

2.3. Sample characteristics and summary statistics

Table 2 presents the descriptive statistics of the internet message board and financial variables used in our analysis. We find that positive sentiment dominates the underlying sentiment on HotCopper. Consistent with existing studies, board message users rather express positive opinions and might want to avoid to speak against their own interest (Antweiler and Frank, 2004; Kim and Kim, 2014; Leung and Ton, 2015). The trend towards positive sentiment also comes along with a high agreement amongst users. Where the Agreement index might take values up to 1, the average Agreement score is 0.925 and in more than half of the firm-days, users agree on their sentiment (median of 1). Average abnormal returns are slightly negative, which might result from larger firms outperforming smaller firms during the sample period and our use of a value-weighted market index similar to Kim and Kim (2014). We find a higher number of analyst downgrade recommendations but a higher number of firm-days with positive earnings surprises on day t during our sample period.

<INSERT TABLE 2 ABOUT HERE>

We segment our event study sample into events triggered by abnormal level of positive or negative sentiment expressed on day *t*. Additionally, we analyze the impact of events with a minimum number of 10 and 20 positive or negative messages on day *t*. Events triggered by Buy/Sell messages sum up to 13,126/493 (minimum 10 messages) and 4,247/100 (minimum 20 messages). Again, the data set implies a high bias towards positive related board messages. For robustness we also test for events with minimum of 30 and 40 messages. The total HotCopper message board data set covers 3,362 stocks (2,700 stocks with at least 100 messages) whereas the trading dataset contains 3,778 stocks between January 2008 and May 2016. We only deleted messages if no trade occurred on the day *t*. The total number of stocks covered in our regression results in 3,050. The regression sample on firm-day level contains 283,585 to 390,842 observations depending on the holding period (30, 10, 5, and 0 days) of the regression. The market capitalization of the stocks with available data has a mean of 691.1 million Australian dollars (AUDs). Similar to our previous study, we find that the majority of stocks discussed on HotCopper can be classified as small stocks, with a median stock capitalization of 19,2 million AUD.

We analyze the causal relationship between (A1) board sentiment and abnormal returns and (A2) message volume and daily price volatility by using (panel) VAR models as well as the Granger causality test on the aggregate and individual stock level. We apply lag order selection tests to determine the optimal lag length for our (panel) VARs. On the aggregate (individual) level, the optimal leg length of 4 (3) for (A1) and 3 (3) for (A2), result in data sets with 380 (42,872) and 797 (42,872) observations, respectively. We construct earnings surprises using analyst forecasts (*SUEAF*) and historical accounting numbers (*SUEHIST*) to examine the value content of internet message boards around annual earnings announcements. We obtain 479 observations (*SUEAF*) and 560 observations (*SUEHIST*) for a cumulative period of one week before the earnings announcement [*t-7, t-1*], respectively.

3. Event Study

Seminal findings of Tetlock (2007) suggest that negative opinions on traditional news media have more pronounced influence on capital market activity. In another study on internet message boards, Chen et al. (2014) find no correlation between positive sentiment and stock returns. Due to the bullishness nature of message boards (Antweiler and Frank, 2004; Leung and Ton, 2015), one might argue that especially negative sentiment contains more value relevant information as internet message board users would like to discuss negative associated firm information in only very specific situations.

Hence, we test the hypothesis that positive and negative sentiment have a significantly different relation to stock market prices and that herding of bullish internet message board users quickly reflects in the market but only remain temporarily influential. Abnormal returns were calculated based on the market excess model in order to examine the relationship between message board activity and abnormal returns. We define an event as a day *t* with abnormal message posting volume (results for at least 10 and 20 buy/sell messages shown in Figure 2 and tabulated in Table 3), where message volume on day *t* exceeds double the standard deviation of message posting volume in the previous five days. We therefore determine an event window of [*t-5; t+5*] and control for overlapping events and thus momentum-induced noise. Consequently, we only include the first event within a seven-day period. On the event day *t*, average cumulative abnormal returns (*ACAR*) are significant for positive and negative sentiment triggered events, however with lower impact for positive related events. Applying the parametric t-test and the non-parametric Wilcoxon-test, we find for event days with a minimum of 20 messages[6] highly significant ACARs of 2.03% (buy-events) and -5.23% (sell-events).

<INSERT FIGURE 2 ABOUT HERE>

<INSERT TABLE 3 ABOUT HERE>

We find significant ACARs of $1.33\%^{min10MSG}$ and $2.03\%^{min20MSG}$ on the event day *t* for positive related events. Of even higher impact, we observe an increasing trend of ACARs from $-3.65\%^{min10MSG}$ to $-5.23\%^{min20MSG}$ on event day *t* for negative messages. In comparison, the median CARs on the event day tend to be significantly lower than the average CARs for both sentiment segments. This indicates that results are driven by particular stocks which are either hyped or negatively talked about in message boards. For events triggered by positive messages, CARs before the event [*t-5, t-1*] are significantly negative ($-1.77\%^{min10MSG}$ to $-1.40\%^{min20MSG}$). We therefore find no indication for a pump and dump behavior, where retail investors built up a long-position before they hype their stocks on social media outlets. In contrast, the results suggest that stocks underperform compared to the market before they get hyped on social media. Furthermore, we find significant negative CARs during the event period [*t+1, t+5*] following the event day *t* from $-4.16\%^{min10MSG}$ to $-6.25\%^{min20MSG}$. These findings support the noise trading theory by De Long et al. (1990). If sentiment rises, noise traders would invest in more risky assets and the uninformed demand drives asset prices above the fundamental value. Subsequently, prices then revert to its fundamental values with associated lower returns in this period which also comes along with excess market volatility (Kim and Kim, 2014).

[6] Robustness tests on events with a minimum of 30 or 40 messages reveal similar results, which are not reported for brevity.

Different to the results surrounding abnormal volume of positive messages, the analysis of negative sentiment indicates another finding. For negative sentiment, ACARs before the event [*t-5, t-1*] are significantly and economically meaningful negative ranging from -6.28%^{min10MSG} to -7.75%^{min20MSG}. Negative peaks of average abnormal returns then follow on the event day t ranging from -3.65%^{min10MSG} to -5.23%^{min20MSG}. Furthermore, we find significant negative ACARs in the event window [*t+1, t+5*] of -6.17%^{min10MSG} and -5.28%^{min20MSG}. The development of the ACARs for negative events indicate that message board users discuss and interpret the negative development of firms. One might argue that message board users especially anticipate the negative momentum of underperforming stocks. The peak of negative abnormal returns on the event day *t* and the absence of return reversals within five days, however imply that message board users may contribute to price discovery by interpreting and analyzing the firm's situation and allow other users to further understand the downward slope of stock price performance.

In summary, the event study findings support our hypothesis that negative message board sentiment has a substantially detrimental relation to abnormal returns and that bullish board users act as noise (uninformed) traders in the market, reinforcing stock price volatility.

4. Predictability of investor sentiment for abnormal returns

We use the following specification to examine the intertemporal relationship between message board activity - in particular the difference between an average and segmented investor sentiment scores - and abnormal stock performance:

$$AbRet_{i,t0,t+j} = \alpha + \beta_1 \, LogMes_{i,t} + \beta_2 \, Bullishness_{i,t} + \beta_3 \, Agreement_{i,t} + \gamma X + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned} AbRet_{i,t0,t+j} = {} & \alpha + \beta_1 \, LogMes_{i,t} + \beta_2 \, PosSentiment_{i,t} + \beta_3 \, NegSentiment_{i,t} \\ & + \beta_4 \, Agreement_{i,t} + \gamma X + \varepsilon_{i,t} \end{aligned} \tag{6}$$

where $AbRet_{i,t0,t+j}$ denotes the difference of compound raw returns and value-weighted market return from day t to $t+j$ (j = 0, 5, 10, and 30 respectively) for firm i. We showed in our previous study, that message board sentiment would be incorporated into stock prices within one month. Thus, we expect a maximum time window of $t+30$ to be sufficient (Leung and Ton, 2015). The general regression specification is based on Chen et al. (2014), but adapted for our research goals. The regression data set contains 283,585 until 390,842 observations on firm-day level depending on the time window. Our main message board variables are defined as follows or already described in section 2: $LogMes_{i,t}$ is the log transformation (1+M_t), $Bullishness_{i,t}$ is the standardized bullishness index defined in formula (1), $PosSentiment_{i,t}$ and $NegSentiment_{i,t}$ describe the positive and negative sentiment denoted in formula (2) and (3), $Agreement_{i,t}$ is the agreement index described in formula (4).

The vector X includes the following control variables: $Volatility_{i,t-30,t-1}$ is the 30-day-standard deviation of returns prior to day t, $Upgrade_{i,t}$/$Downgrade_{i,t}$ describe the number of analyst upgrade/downgrade recommendation on day t, $PosMeanES_{i,t}$/$NegMeanES_{i,t}$ denote dummy variables for positive/negative mean earnings surprise on day t. We further include $AbRet_{i,t-1}$, $AbRet_{i,t-2}$, and $AbRet_{i,t-j,t-1}$ to control for possible autocorrelation. Lastly, we include the interaction terms $SentimentHom_{i,t}$ ($Bullishness_{i,t}$ x $Agreement_{i,t}$) for sentiment homogeneity and $LogMes$ x $Vola_{i,t}$ ($LogMes_{i,t}$ x $Volatility_{i,t-30,t-1}$). Due to the broad variety of observed firms in our data set, we assume significant cross-sectional differences in message posting volumes as well as firm-characteristics. We therefore use firm-fixed effects for each stock in our regressions[7]. Additionally, we use clustered standard errors by firm and year to account for the lack of independence in firms' abnormal returns (heteroscedasticity), as well as serial- and cross-correlation. This approach is consistent with the method used by Petersen (2009).

<INSERT TABLE 4 ABOUT HERE>

Results of the regression are tabulated in Table 4. The analyst based coefficient estimates of the control variables are generally in line with our expectations. For $AbRet_{i,t0,t+30}$ (column 10) we find positive estimates for $Upgrade_{i,t}$ and $PosMeanES_{i,t}$. and negative (significant) values for $Downgrade_{i,t}$ and $NegMeanES_{i,t}$. In general, we find that message volume is significantly negative and the average bullishness/agreement index is significantly positive associated with abnormal returns throughout our observed holding periods. Applying segmented sentiment, the significance of positive sentiment diminishes after 30 trading days but for negative sentiment, the coefficient estimates remain highly significant with increasing impact (from $\beta_{t0}^{NegSentiment}$= -0.010 to $\beta_{t0,t+30}^{NegSentiment}$ = -0.032). Therefore, the significance of the average bullishness index is mainly driven by negative sentiment. Similar to Tetlock (2007) for traditional media and Chen et al. (2014) for social media, we find evidence on the predictive power of negative sentiment shared on internet message boards. We also do find a significant positive correlation between positive sentiment and abnormal returns until the holding period of 10 trading days with $\beta_{t0,t+j}^{PosSentiment}$ ranging from +0.006 to +0.012. The effect however diminishes after 30 trading days and speaks for a return reversal and the theory of noise trading. To shed light on the economic significance of our results, we calculate the impact of an one standard

[7] To test the robustness of the fixed-effect vs. the random-effect model we have conducted the Hausman-specification test on the panel data. Results confirmed the validity of the fixed-effect regression model specification. Results are not tabulated here.

deviation increase in negative (positive) sentiment variables on a firm's abnormal returns and we find an contemporaneous decrease (increase) of -0.38%-points (0.59%-points) and a remaining impact of -1.22%-points (0.00%-points) after 30 days. Hence, we find empirical evidence on a remaining economically meaningful and significant impact of negative sentiment on a firm's abnormal returns.

Another implications from our regressions are that $Bullishness_{i,t}$ and $Agreement_{i,t}$ are dependent on each other: the significant coefficient of the interaction term $SentimentHom_{i,t}$ implies the higher the $Agreement_{i,t}$ the higher the impact of $Bullishness_{i,t}$ on abnormal returns, and vice versa. Furthermore, volatility significantly predicts future abnormal returns. Negative realized volatility is significantly negatively related to $AbRet_{t0.}$ The significance reverts to a positive relationship for subsequent holding periods. To also examine the connection between realized volatility and the message volume, we include the interaction term $LogMes\ x\ Vola_{i,t.}$ At first, the interaction term $LogMex\ x\ Vola_{i,t}$ is slightly positively significant for the contemporaneous regressions, with an coefficient of about +0.062 for all specifications. The relation then reverts into negative and becomes highly significant for a holding period of 30 trading days with coefficients of around -0.390 for all specifications. This suggests that the higher the number of posted messages on day *t* the lower the impact of volatility of the past 30 trading days, $Vola_{i,t\text{-}30,t\text{-}1,}$ on the future abnormal returns, and vice versa.

<INSERT TABLE 5 ABOUT HERE>

We also repeat the regressions for our sample divided in to large and small capitalization stocks (see Table 5 results). Consistent with Leung and Ton (2015), results show that estimates of the internet message board variables are stronger for small capitalization stocks. For robustness and to test the extent to which our results might have been affected by sparseness of message postings by different firms, we conducted the same regressions on a data set with firm-days with at least 10 relevant buy or sell messages a day. The overall structure and pattern remained stable (results are not tabulated here but available upon request).

In summary, our regression findings provide empirical evidence that average and segmented sentiment scores must be treated differently and that opinions expressed via finance related social media outlets contribute to price discovery for firms experiencing negative abnormal return momentum but also induce positive shocks which may be attributed to the outcome of noise trading. However, the causal explanation if sentiment leads stock performance or vice versa cannot be clearly answered.

4.1. Intertemporal predictability of message board sentiment and abnormal returns

We apply a Vector Auto Regression model (VAR) on the aggregate and on the individual firm level (panel VAR[8]) to investigate the causal relationship between message board sentiment and abnormal returns and attempt to address the endogeneity issues, in specific the simultaneous impact of sentiment and a firm's performance compared to the market, in the data.

4.1.1. Sentiment and abnormal returns at the aggregate level

<INSERT TABLE 6 ABOUT HERE>

We compute the optimal lag length and apply it to the most valid lead-lag regression specification. Results are reported in Table 6. Three out five tests indicate that a lag structure of four fits best for our model. Only the Hannan-Quinn information criteria and the Schwarz information criteria imply an optimal lag structure of 3 and 2, respectively. Hence, we construct our VAR model based on four endogenous lags to closer examine the causal relationship between the segmented sentiment and abnormal returns. We consider the following three equations to test the intertemporal interaction of sentiment and abnormal returns:

$$AbRet_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j}, AbRet_{t-j} + \sum_{j=1}^{L} \gamma_{1,j}, PosSent_{t-j} + \sum_{j=1}^{L} \delta_{1,j}, NegSent_{t-j} + \varepsilon_{1t} \tag{7}$$

$$PosSent_t = \alpha_2 + \sum_{j=1}^{L} \beta_{2,j}, AbRet_{t-j} + \sum_{j=1}^{L} \gamma_{2,j}, PosSent_{t-j} + \sum_{j=1}^{L} \delta_{2,j}, NegSent_{t-j} + \varepsilon_{2t} \tag{8}$$

$$NegSent_t = \alpha_3 + \sum_{j=1}^{L} \beta_{3,j}, AbRet_{t-j} + \sum_{j=1}^{L} \gamma_{3,j}, PosSent_{t-j} + \sum_{j=1}^{L} \delta_{3,j}, NegSent_{t-j} + \varepsilon_{3t} \tag{9}$$

where $AbRet_t$ is the equally-weighted abnormal return and $PosSent_t/NegSent_t$ the aggregated sentiment level of the 3,050 sample stocks at time t between January 11th, 2008 and May 27th, 2016. We apply the lag exclusion χ^2 Wald-tests on each lag in the VAR to test whether aggregated investor sentiment Granger-cause aggregated abnormal stock returns or vice versa. The first two null hypothesis are therefore $H_{1/2}$: $\gamma/\delta_{1,1} = \gamma/\delta_{1,2} = \ldots = \gamma/\delta_{1,L} = 0$, implying that aggregated positive/negative sentiment does not Granger-cause aggregated future abnormal stock returns. The third and fourth null hypothesis of interest are $H_{3/4}$: $\beta_{2/3,1} = \beta_{2/3,2} = \ldots = \beta_{2/3,L} = 0$, indicating that aggregated abnormal stock

[8] Based on the model by Abrigo and Love (2015)

returns do not Granger-cause aggregated positive or negative sentiment, respectively. Table 7 shows the results for our lag 4 VAR specification.

<INSERT TABLE 7 ABOUT HERE>

For comparison, we additionally show results for the lag 2 VAR. The coefficient estimates for equation (7) and for the aggregated positive and negative sentiment variables are only highly significant for the negative sentiment on the previous day ($\gamma_{1,1}$ = -0.065). The p-value of the χ^2-test statistics for H_2 is 0.000 and the hypothesis that aggregated negative sentiment does not Granger-cause aggregated abnormal stock returns must therefore be rejected. In line with former results, we also find a negative relationship in equation (7) for positive sentiment on the previous day and abnormal returns which is line with the return reversal observed in the event study, even though not found significant here. On the aggregate level, we thus find indications that negative sentiment predicts abnormal returns and that aggregated positive sentiment has no Granger-relation to aggregated abnormal returns.

4.1.2. Sentiment and abnormal returns at the individual level

To further examine the individual Granger-relationship between investor sentiment and abnormal returns on the individual level, we perform a panel vector auto-regression. Hence, we also test the hypothesis H_{1-4} on the individual level. Based on the test for optimal lag length for the panel data, we use the lag of 3 for the panel VAR. For comparison, we also show the results for lag 2 and 4 of the panel VAR in Table 8.

<INSERT TABLE 8 ABOUT HERE>

Results on individual level compared to aggregate level show different implications on the Granger-relationships: Positive sentiment significantly predicts abnormal returns at the significance level of 5% with coefficient estimates of -0.002 and +.0.001 for *t-1* and *t-3*, respectively (see Table 8, column 2). This result is in line with our event study which suggests that abnormal return reversals occur the day after an event day of abnormal positive sentiment. Additionally, results in Table 8 (column 5) show that coefficient estimates ($\beta_{2,t-1}$ = +0.301 and $\beta_{2,t-3}$ = -0.212) for abnormal returns are highly significant at 1%-level, which indicates that abnormal returns predict positive sentiment only for the subsequent day. The χ^2-test statistics for H_1 of 52.271 (p-value = 0.000) are higher than for H_3 with 12.910 (p-value = 0.005), yet both hypothesis can be rejected at the significant level of 1%. These results imply that positive sentiment and abnormal returns both Granger-cause each other, however with larger impact from abnormal returns on positive sentiment. In other words, message board users rather react to abnormal return shocks, but also provide (noisy) information which are then incorporated into abnormal returns, albeit of smaller economic impact.

For negative sentiment and abnormal returns, however, we do not find a Granger-relationship based on the optimal lag length 3. The Granger-causality Wald-test cannot reject the hypothesis H_2 and H_4. As we look at the results for a lag of 2 (Table 8, column 1), the coefficient estimate for $\delta_{1,t-1}$ of -0.003 is highly significant and the χ^2 Wald-test rejects hypothesis H_2 which means that negative sentiment Granger-causes abnormal returns and not vice versa. We expect that this difference results from the data structure and the dominance of bullishness in the data set. Since negative related messages are less present on the HotCopper internet message board, we believe that the lag order of 3 and the smaller data set results in insignificance.

We find strong evidence that negative sentiment Granger-causes aggregated abnormal returns. This suggests that the aggregated sentiment level of message board users is able to predict market movements. Secondly, we find that positive sentiment and abnormal returns Granger-cause each other on individual level, yet with significantly larger impact from abnormal returns to positive sentiment. Therefore, message board users rather react to market activity but also disseminate information that move stock prices. The predicted abnormal return reversal after positive messages on the subsequent day also speaks for the noise trading theory by De Long et al. (1990), where stock prices are moved away from fundamentals but then return to the real fundamental value. For negative sentiment, we find on individual level and based on the optimal lag length of 3 for the whole panel data set that negative sentiment is not Granger-related to abnormal returns. However, as we reduce the lag length to 2, we observe that negative sentiment predicts abnormal returns on individual stock level. This effect might be induced by the structure of the strongly positively biased data set.

We apply the impulse response analysis to examine the dynamic interaction between the endogenous variables ($Abret_t$, $PosSent_t$ and $NegSent_t$) of the panel VAR process. For the validity of the panel VAR application, we first test on stability of the panel VAR process. Please refer to specific econometric studies for detailed explanation of the model (Sims, 1980; Hamilton and Susmel, 1994; Lütkepohl, 2005). As stability implies stationarity of the VAR model, we can find an infinite-order vector moving-average (VMA) representation, which is needed for the interpretation of impulse-response functions. Consider that equations (7) - (9) can be formulated as:

$$Y_{i,t} = C_0 + Y_{i,t-1}A_1 + Y_{i,t-2}A_2 + \cdots + Y_{i,t-L}A_L + \varepsilon_{i,t} \tag{10}$$

where $Y_{i,t}$ is a ($1 \times n$) vector of the endogenous variables, $A_1, A_2, \ldots, A_L$ are ($m \times n$) coefficient matrices and $\varepsilon_{i,t}$ is a ($1 \times n$) vector of error terms. The panel VAR process is stable when the moduli of all eigenvalues of the companion matrix $\bar{A}$ are less than 1.

The companion matrix is defined as:

$$\bar{A} = \begin{bmatrix} A_1 & A_2 & \dots & A_L & A_{L-1} \\ I_n & 0_n & \dots & 0_n & 0_n \\ 0_n & I_n & \dots & 0_n & 0_n \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0_n & 0_n & \dots & I_n & 0_n \end{bmatrix} \tag{11}$$

where I_n is the identity ($n \times n$) matrix. Our robustness tests show that all moduli of the eigenvalues of $\bar{A}$ are strictly less than 1 and thus account for stability of our panel VAR process (results are not tabulated here). Based on the work of Abrigo and Love (2015), we apply the Cholesky impulse-response function, to address the issue that the error terms e_{it} might be contemporaneously correlated.

The Cholesky adaption is based on the simple impulse-response function Φ_i, which can be expressed as an infinite vector-moving average with the following VMA specifications[9]:

$$\boldsymbol{\Phi_i} = \begin{cases} \boldsymbol{I_n} \quad , & \boldsymbol{L = 0} \\ \sum_{j=1}^{L} \boldsymbol{\Phi_{t-j} A_j} \, , & \boldsymbol{L = 1, 2, ..} \end{cases} \tag{12}$$

Figure 3 depicts the results of the impulse response function based on equation (10). We focus on the dynamic interaction of positive/negative sentiment and abnormal returns. Abnormal returns show no contemporaneous reaction to negative sentiment shocks but negative peaks occur after a period of 4 days and successively disappear. Positive sentiment shocks lead to a negative peak of abnormal returns on the following day, also in accordance to former event study and regressions results in section 3 and 4. This again indicates a negative market reaction on the subsequent day, however we do not observe a contemporaneous market reaction. A reason could be that a high number of board messages are posted after the closing hours of the ASX as shown in Figure 1. Another reason could be, when experiencing positive sentiment shocks, message board users then trade regardless of their informational situation. Bloomfield et al. (2009) distinguish noise traders between liquidity traders, who trade due to unexplained liquidity reasons, and uninformed traders, who might trade despite having no advantages in information or other exogenous motivational reasons to trade. Liquidity based trading would be the nearest explanation for the negative abnormal return on the day following positive sentiment shocks and thus induce volatility in the market.

<INSERT FIGURE 3 ABOUT HERE>

Abnormal returns shocks come with different impact. We observe contemporaneous responses of negative and positive sentiment to abnormal return shocks with gradually decreasing impact, yet with larger response magnitudes for positive sentiment. In line with our expectations, negative abnormal

[9] We run our statistical analysis with the panel VAR STATA package by Abrigo and Love (2015)

return shocks come along with negative responses for negative sentiment whereas positive abnormal return shocks come along with positive sentiment responses. We interpret these findings as follows: Message board users tend to react to abnormal returns shocks. For negative abnormal returns shocks, message board users intensify their research on recent developments and future expectations, contribute and may add valuable information to the price discovery process.

In summary, our impulse response function results confirm our prior findings that negative and positive sentiment have differentiated relation to stock market performances. Negative abnormal return responses to negative sentiment shocks show a 4-day delay while positive sentiment shocks lead to a negative abnormal return response on the subsequent day. On the other hand, message board sentiment contemporaneously reacts to abnormal return shocks. Negative abnormal returns follow positive sentiment shocks, prefiguring preceding trading activities of noise traders in equities markets.

4.2. Informed short selling against positive noise traders

Previous results in this paper show a contemporaneous positive relationship between positive sentiment and a firm's abnormal returns with subsequent return reversals. This indicates that trades were dominated by sentimental traders who show propensity to either speculation or over-optimism (Baker and Wurgler, 2007). Prior literature argued that misevaluation of asset prices can only be partially offset by contrarian arbitrageurs or in specific cases (un-)informed short sellers. The high costs and risks associated with betting against sentimental investors (Shleifer and Vishny, 1997) could lead to the conclusion that for example rather only well informed short sellers would bet against overpriced stock movements, which are driven by sentimental investors (Diamond and Verrecchia, 1987). We therefore believe that stocks which are hyped on internet message boards and are also targeted by informed short sellers are less prone to experience a positive abnormal return shock with following return reversals. Hence, we conduct the same regressions as in section 4, based on equation (6) and furthermore include the variable $PercShort_{i,t}$ and the interaction terms $PercShort \ x \ PosSentiment_{i,t}$ and $PercShort \ x \ NegSentiment_{i,t}$. $PercShort_{i,t}$ describes the ratio between the number of reported short positions and the number of shares outstanding on stock *i* and day *t.* The results are tabulated in Table 9.

<INSERT TABLE 9 ABOUT HERE>

In line with prior literature, we find that the share of short selling positions negatively and significantly predicts abnormal returns (e.g., Figlewski and Webb, 1993 Aitken et al., 1998). The contemporaneous relationship between $PercShort_{i,t}$ and a firm's abnormal return is at first slightly positive but then reverts into negative for the time period of 30 days. One reason could be that informed sellers rather target overvalued stocks. Since the ASIC publishes the total short positions for financial products only four days after reporting[10], one should expect a time-lag of the negative impact of short selling positions on a stock's excess returns. Due to the concern that our results might by affected of trading days with only little message board activity, we conduct the same regressions only including observations with a minimum of 10 and 20 messages on day *t*. The direction of our results remain robust even though the results are less or not significant anymore.

Additionally, we find a significantly negative relationship between positive sentiment expressed on internet message boards and short selling positions on stock *i* on day *t* (negative interaction term $PercShort\ x\ PosSentiment_{i,t}$). The magnitude of the coefficient increases as we conduct our regressions with a minimum level of message board activity on stock *i* on day *t*. This finding implies that a higher ratio of short position of a firm reduces a possible overreaction of a stock's abnormal return on positive sentiment expressed on internet message boards. We therefore find empirical evidence that short selling reduces the impact of (positive) sentimental investors on the same day. From the economic point of view, it seems unlikely that our dependent variable, the abnormal return, causes short selling activity. However, we finally cannot eliminate the possibility of confounding events which motivate a short seller to build up that position.

4.3. Volatility and message board activity

We have argued in former sections that the activity of noise traders, be it due to liquidity or other exogenous reasons, induce volatility in the market. To closer understand the drivers behind volatility, we first regress volatility against the message board variables including the market return as a control variable for different time periods following Antweiler and Frank (2004). Results are tabulated in Table 10. We find that all three message board variables are significantly related to volatility. The message volume reveals significant coefficient estimates of +0.033 and +0.022 for the period *t* and *t+1* at the significant level of 1%.

<INSERT Table 10 ABOUT HERE>

The bullishness index in general has a negative impact on volatility with an also highly significant coefficient estimate of about -0.005. Agreement seems to be important in the time window of *t+1* to *t+30* with a coefficient of +0.005. It appears that the message volume has the largest impact on market

[10] Please see http://asic.gov.au/regulatory-resources/markets/short-selling/short-selling-reporting-short-position-reporting/ as of September 17th, 2017

volatility. To further examine the causal relationship between message board activity and market volatility, we conduct a VAR analysis in the next section.

4.4. Intertemporal predictability of message board activity for market volatility

4.4.1. Message volume and volatility at the aggregate level

To examine whether message board activity forecast next-periods stock price volatility and to assess how these two variables interact intertemporally (short-term), we consider the following two equations:

$$Vola_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j}, Vola_{t-j} + \sum_{j=1}^{L} \gamma_{1,j}, LogMes_{t-j} + \varepsilon_{1t} \quad (13)$$

$$LogMes_t = \alpha_1 + \sum_{j=1}^{L} \beta_{2,j}, Vola_{t-j} + \sum_{j=1}^{L} \gamma_{2,j}, LogMes_{t-j} + \varepsilon_{1t} \quad (14)$$

where $LogMes_t$ is the equally-weighted message board activity at time *t* and $Vola_t$ is the equally-weighted stock price volatility of the 3,050 sample stocks at time *t*. Based on the test on the optimal lag length, we apply a lag of 3 (results reported in Table 11).

<INSERT Table 11 ABOUT HERE>

Results for the VAR model on the aggregated level are shown in Table 12. The null-hypothesis (H_5) that: $\gamma_{1,1} = \gamma_{1,2} = \gamma_{1,3} = 0$ from equation (13) cannot be fully rejected with a p-value of the χ^2-test statistic for H_5 of 0.395. However, the p-value of the χ^2-test statistic for H_6 is 0.093. The null-hypothesis (H_6) that: $\beta_{2,1} = \beta_{2,2} = \beta_{2,3} = 0$ from equation (14) can therefore be rejected at the 10%-signifiance level. In another words, the Granger-causality tests indicate that message board activity on the aggregate level may be positively Granger-caused by prior stock price volatility.

<INSERT Table 12 ABOUT HERE>

4.4.2. Message volume and volatility at the individual level

We perform a panel VAR following an impulse response analysis to further examine the individual Granger-relationship between message board activity (volume) and stock price volatility at the individual level. We first test the hypothesis H_5 and H_6 on the individual level. Based on the test for optimal lag length for the panel data, we use the lag of 3 for the panel VAR. For comparison, we also show the results for lag 2 and 4 of the panel VAR in Table 13.

<INSERT Table 13 ABOUT HERE>

We find for the optimal lag length of 3, that the previous day message board volume significantly predicts volatility, however with an economically small impact (coefficient estimate of +0.004). On the other hand, we also observe that previous days volatility strongly predicts message board activity even though with changing signs ($\beta_{2,3} = -0.124, \beta_{2,2} = -0.249$ and $\beta_{2,1} = +0.483$). Both χ^2-test statistics for H_5 of 51.632 (p-value = 0.000) and for H_6 of 66.607 (p-value = 0.000) are highly significant so that both hypotheses can be rejected. In other words, message board volume and stock price volatility Granger-cause each other. Nevertheless, we can conclude the reaction of message board volume to stock market volatility is significantly higher than vice versa.

We again apply the Cholesky based impulse function to also examine the dynamic interaction of message board volume and stock price volatility. Figure 4 shows the corresponding results. Stock price volatility reacts to message board volume shocks on day *t+1* with decreasing but remaining impact after 10 days. Setting a one standard deviation volatility shock, we observe a considerably high contemporaneous message board activity response compared to the other direction. Our results suggest, that message board activity rather follows market volatility, even though message board activity might induce stock price volatility albeit of small economic impact.

<INSERT FIGURE 4 ABOUT HERE>

5. Fundamental Information in Internet Message Boards around Company Events

The differentiated impact of social media activity found in our event study (Figure 2) and in our multivariate analysis underlines its importance in capital markets. Despite our different steps taken (event study, (panel) VAR, multivariate regressions), we cannot clearly argue in general whether social media users act as noise traders, who move prices away from their fundamentals, or convey financially relevant information and thus contribute in price discovery. Consequently, researchers must also distinguish between the impact of social media in non-event and event specific environments. Thus, we now examine the cross-sectional relationships between the message board variables and fundamental values around annual earnings announcements.

Financial analysts act as important intermediaries in equities markets and are subject to a broad body of research streams. Two main reasons of existence come along with their role: the discovery of private information and furthermore the interpretation of publicly available information (Ivković and Jegadeesh, 2004; Asquith et al., 2005; Chen et al., 2010). Chen et al. (2014) argue that annual earnings reported by firms are probably not affected by social media activity. Since it would also be unlikely that financial analysts revise their recommendations based on negative sentiment (therefore negative sentiment would predict negative earnings surprise), social media would represent an information channel with predictive power. They found that negative opinions revealed on the investment-related platform Seeking Alpha predict future negative earnings surprises. One of the main disadvantages of looking at analyst forecasts is the sole reflection of analysts opinions, rather than the consideration of market information, which could be available to other well-informed market participants (Akbas, 2016). Attributable to the area of Behavioral Finance, opinions might be subject to a positive bias as financial analysts encounter the desire to conform, in other words "herd" (Olsen, 1996). Herding characteristically moves the mean Earnings per Share (EPS) forecast towards a specific direction and lowers the forecast dispersion. Former studies showed that analysts forecasts have rather been over optimistic compared to the actual reported EPS (Olsen, 1996). A reinforcing factor is also, that financial analysts are judged by their degree of conformity with other analyst forecasts, since the quality of forecasts is exposed to uncontrollable exogenous factors. A consensus forecast is therefore in interest to all analysts in order to protect their right for existence and thus their human capital (Scharfstein and Stein, 1990; Trueman, 1994; Froot et al., 1992; Olsen, 1996). Hence, we argument that if financial analyst releases optimistic consensus recommendations and social media users agree in the optimistic outlook of the firm's performance then earnings surprises might be rather positive.

Based on the work of Chen et al. (2014) and Akbas (2016), we conduct a firm-fixed regression of annual earnings surprises on message board variables and various control variables to examine the value-content of internet message boards. Our model extends the approach of Chen et al. (2014) by additional consideration of positive sentiment and the degree of agreement in message board discussions (or sentiment homogeneity). If message board activity would not contain value-relevant information, then no relationship should exist between earnings surprises and our message board variables. However, our results clearly suggest that social media does provide financially relevant information in event-specific environments. For comparison, we constructed two different types of earnings surprises as our dependent variable. The standardized unexpected earnings surprise based on analyst forecasts (*SUEAF*) and the standardized unexpected earnings based on the historical time series information (*SUEHIST*).

The standardized unexpected earnings (*SUEAF*) based analyst forecasts is defined as:

$$SUEAF_{i,t} = \frac{(\,X_{i,t} - Xmed_{i,t-90d})}{P_{i,t}} \tag{15}$$

where X_{it} is the primary Earnings per Share (EPS) before significant items for firm *i* in financial year *t* and $Xmed_{i,t-90d}$ is the EPS-median of most recent analyst forecasts over 90 days prior to the annual earnings announcement, and $P_{i,t}$ is the price per share for firm *i* at the end of the financial year *t* from I/B/E/S. To eliminate the impact of outliers, we winsorized the top and bottom 1% of the observations.

The standardized unexpected earnings based on the random walk model (*SUEHIST*) is as follows:

$$SUE_{it} = \frac{(X_{i,t} - X_{i,t-1})}{P_{i,t}} \tag{16}$$

where $X_{i,t-1}$ is the primary earnings per share (EPS) before significant items for firm i in the previous financial year. For our control variables and following Akbas (2016), we first include Ret_{50}, the compounded return over the period of 50 days [*-61,-12*] days prior to the earnings announcement date and Ret_5 for the 5-day return period [*-6,-2*] prior to the earnings announcement date. We also include $Volatility_{i,10}$ which is the standard deviation of daily returns in the time window [*-11,-2*] prior to the earnings announcement. Next, we include the log-transformed average turnover $LogTurnover_{i,50}$ over the time window [*-61,-12*] to account for potential average volume effects as stated by Berkman et al. (2009). Additionally, we add the log-transformed market capitalization $LogSize_{i,t}$, which is the log-transformation of shares outstanding times the share price at the end of the financial year. This also accounts for skewness in the data set (small capitalization stocks are predominant in the data set as described in section 2). Lastly, we include cumulated message board variables $LogMessages_{i,[RP]}$, $Bullishness_{i,[RP]}$, *PosSentiment/NegSentiment* $_{i,[RP]}$ and *Agreement* $_{i,[RP]}$ with the daily-based reference periods (RP) of [*-2,-1*], [*-7,-1*], and [*-30,-1*] to measure the information content over a sufficient time horizon.

Table 14 reports the summary statistics for the message board time period of [*-7,-1*] days before the earnings announcement based on analyst forecasts. We find a mean of -0.014 for scaled earnings surprise (*SUEAF*) which supports the argument that analysts tend to herd and are too optimistic in their consensus forecast.

<INSERT Table 14 ABOUT HERE>

In former literature, researchers link (excess) trading volume to divergence in investor opinion (Beaver, 1968; Bamber, 1987; Kandel and Pearson, 1995; Garfinkel and Sokobin, 2006). As we hypothesis that opinion convergence would on the other hand contribute to price discovery we can directly refer to the sentiment expressed in the internet message board instead of using trading volume as a proxy. Figure 5 shows the development of the cumulated agreement index before the earnings announcement date *t*. For the event window of 7 days prior the announcement date [*-7,-1*], we cumulated all financially relevant board messages (sell and buy recommendations) and constructed the agreement index based on formula (4). We find an agreement convergence pattern towards a high degree of agreement on sentiment as we approach the earnings announcement date with event windows of [*-60,-1*], [*-30,-1*], [*-7;-1*] and [*-2,-1*]. In other words, message board users agree more and more in their sentiment as they discuss firm fundamentals before annual earnings announcements. However, we cannot clearly observe whether message board users become convinced by other opinions or whether disagreeing users leave the discussion. As DeMarzo et al. (2003) pointed out, the main prerequisites for the convergence of beliefs are that investors may not be isolated from each other and that their beliefs are not fixed in a sense that discussions would stop. Social media platforms enable retail investors to participate in discussions rather than isolating its users in distinctive discussions. Hence, social media generally meet the first requirement for belief convergence. However, it is not clear how message board users with fixed believes interaction in their discussions. We take a closer look at the cross-sectional impact of sentiment on agreement on earnings surprises in the next section.

<INSERT FIGURE 5 ABOUT HERE>

5.1. Portfolio analysis

Akbas (2016) argues that extraordinary low trading volume contains unfavorable information about a firm's fundamentals, since informed investors would not trade – given short selling constraints – based on the bad information they have. We believe that the direct measure of agreement combined with the underlying sentiment – we define it sentiment homogeneity –would also act as a signal of bad news of a change in firm's fundamentals, equivalent to the abnormal low trading volume found by Akbas (2016). This view is also supported by the 'no trade' theory as suggested by Milgrom and Stokey (1982), in which disagreement (which is in this case connected to low trading volume) prevent investors from trading. Hence, we constructed a portfolio and assigned the stocks to quartiles based on the *sentiment homogeneity* ($Agreement_{i,t}$ x $Bullishness_{i,t}$). Figure 6 depicts the average earnings surprise using on analyst forecasts (*SUEAF*) for each quartile. The mean *SUEAF* for quartile 4 is significantly negative with -2.6% at the 5%-significance level. For quartile 3, we find a negative mean *SUEAF* of -3.8% and it is significant at the 10% level. The mean *SUEAF* turns into positive for quartile 1, however not found significant anymore. The difference of -2.9% between quartile 4 (lowest sentiment homogeneity) and 1 (highest sentiment homogeneity) is significant at the 5% level, based on the Satterthwaite method. The trend depicted in Figure 6 thus suggests that low levels of sentiment homogeneity (or sentiment heterogeneity) convey negative information about earnings surprises. High levels of sentiment homogeneity on the other hand contains positive information about a firm's fundamentals, however not found significant. The general findings are as expected, however one cannot clearly argue if negative (positive) sentiment or high level of disagreement (agreement) convey negative information about future earnings surprises. Both variables must be treated jointly in this discussion. Yet, the results are prone to the interpretation of the underlying earnings surprises and the question whether analysts had been overly optimistic due to analyst herding. This question is a topic in a strand of literature (Scharfstein and Stein, 1990, Trueman, 1994) and not answered in this study.

<INSERT FIGURE 6 ABOUT HERE>

5.2. Regressions on earnings surprises

In this section, we conduct a cross-sectional fixed-effect regression with firm-year clustered standard errors on *SUEAF* and *SUEHIST* to analyze the relation between message board variables and earnings surprises while controlling for factors that may affect this relation. The starting point of the regressions (see results in Table 15, column 1) is as follows:

$$\begin{aligned} SUEAF_{i,t}\ /\ SUEHIST_{i,t} \\ &= \alpha_t + \beta_{1,t} LogMessage_{i,7} + \beta_{2,t} Bullishness_{i,7} + \beta_{3,t} Agreement_{i,7} \\ &+ \gamma_1 LogSize_{i,t} + \gamma_2 Volatility_{i,10} + \gamma_3 Return_{i,50} + \gamma_4 Return_{i,5} \\ &+ \gamma_5 LogTurnover_{i,50} + + \varepsilon_{i,t} \end{aligned} \tag{17}$$

The main message board and control variables are described in the previous section. We perform the regression for both types of earnings surprises, $SUEAF_{i,t}$ and $SUEHIST_{i,t}$ to examine whether retail investors on social media relate to specific events or information in their discussions. If retail investors developed to sophisticated well-informed investors, then we would expect them to acquire the most relevant financial analyst reports before the earnings announcement. The main variables of interest are the message board related variables (incl. interaction terms). We then add the interaction term for sentiment homogeneity ($BullInd\ x\ AgreeInd_{i,7}$) to test the joint relation with earnings announcements. Results are tabulated in Table 15.

<INSERT Table 15 ABOUT HERE>

For $SUEAF_{i,t}$, the results show that the coefficient estimates for bullishness (agreement) is negative (positive) and significant at the level of 10% (5%) in the basis regression (Table 15, column 1). By adding the interaction term $SentimentHom_{i,t}$,, we find a positive relation between sentiment homogeneity and $SUEAF_{i,t}$ with a positive coefficient estimate of +0.082 which is significant at the 1% level (Table 15, column 3). In other words, the higher the bullishness, the higher the impact of agreement on $SUEAF_{i,t}$, and vice versa. Investors using social media relate information from analyst reports with their newest findings and analysis. Information about changes of a firm's fundamental are discussed and results suggest that situations in which investors are rather bullish and agreed result in higher earnings surprises. One must consider, that social media users in our analysis could have a timing advantage against financial analysts, since we consider analyst reports of the past 90 days for our earnings surprise calculation. Since our results only hold for the time window of [*-7,-1*], we can assume that retail investors on social media have sufficient time to access older reports and invest effort to interpret and extent the information content of the report. The overall regression results in this section are in line with our previous finding in the portfolio section that sentiment homogeneity provides significant signals for earnings surprises.

The results for $SUEHIST_{i,t}$ on the other hand did not show any relevant significance for message board variables. Our results therefore suggest that retail investors on social media are important market participants who disseminate value-relevant information around annual earnings announcements. They discuss, interpret and disseminate information depending on the type of event, sentiment and agreement among the users.

6. Conclusion

We investigate the differential information content of internet message boards in non-specific event setups and surrounding annual earnings announcements. We first find that positive sentiment is positively related to abnormal returns but the effect diminishes after a month. In the short term, the relation holds in both directions but with implications that positive sentiment rather follows the previous day excelling stock performance. Furthermore, we observe a pattern of noise trading activity surrounding events with abnormal positive sentiment postings. More specifically, abnormal returns are positively contemporaneously associated with abnormal positive sentiment postings, however with negative return reversals on the subsequent days. This presumably observed contemporaneous overreaction in firm's abnormal return is reduced by short selling activities.

We argue that only informed sellers initiate short selling activities when they believe that sentiment diverges far beyond a firm's fundamentals. Hence, short sellers arbitrage against noisy sentiment traders. However, due to limits of arbitrage and hyping of rather small stocks we do see a remaining contemporaneous relation between positive sentiment and a firm's abnormal returns. Secondly, we find that negative sentiment incorporates information about stock underperformances with negative correlation of up to one month as analyzed in this paper. Contrary to the characteristics of positive sentiment postings, we find indications that negative sentiment predicts the underperformance of stocks compared to the market in the short-term. Abnormal return reversals into positive remain absent after days of abnormal high postings with negative sentiment. The impact of negative sentiment is thereby much more economically meaningful compared to messages with positive sentiment. As the questions arises if social media might induce market volatility, we thirdly find that increased internet message board postings are rather caused by previous stock price swings than vice versa. Even though our findings imply a bilateral-direction in causality, the impact of message board activity on volatility reveals modest economic significance. Lastly, our findings provide evidence that message board sentiment and agreement – or sentiment homogeneity - amongst the users predict earnings surprises using analyst forecasts. This is in line with former studies (Chen et al., 2014; Leung and Ton, 2015) which propagate the dissemination of value-relevant information through internet message boards or social media outlets.

We summarize our findings that internet message boards as an outlet of social media have a substantial impact on equities markets however with significant differential effects depending on the sentiment and on the surrounding events. Additionally, regulators should succumb to the discussion whether arbitrageurs contribute to the price stabilization process especially in noisy market environments.

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FIGURES

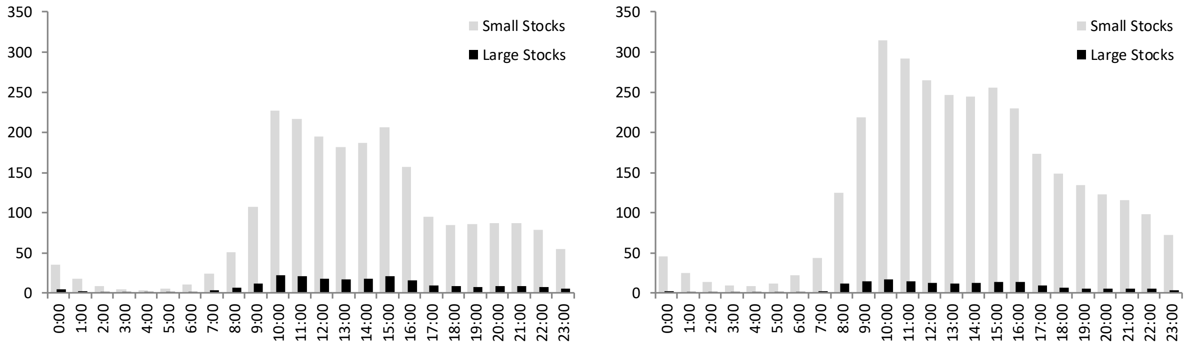

Figure 1. Message postings (in thsd.): 2003-2008 vs. 2008-05/2016

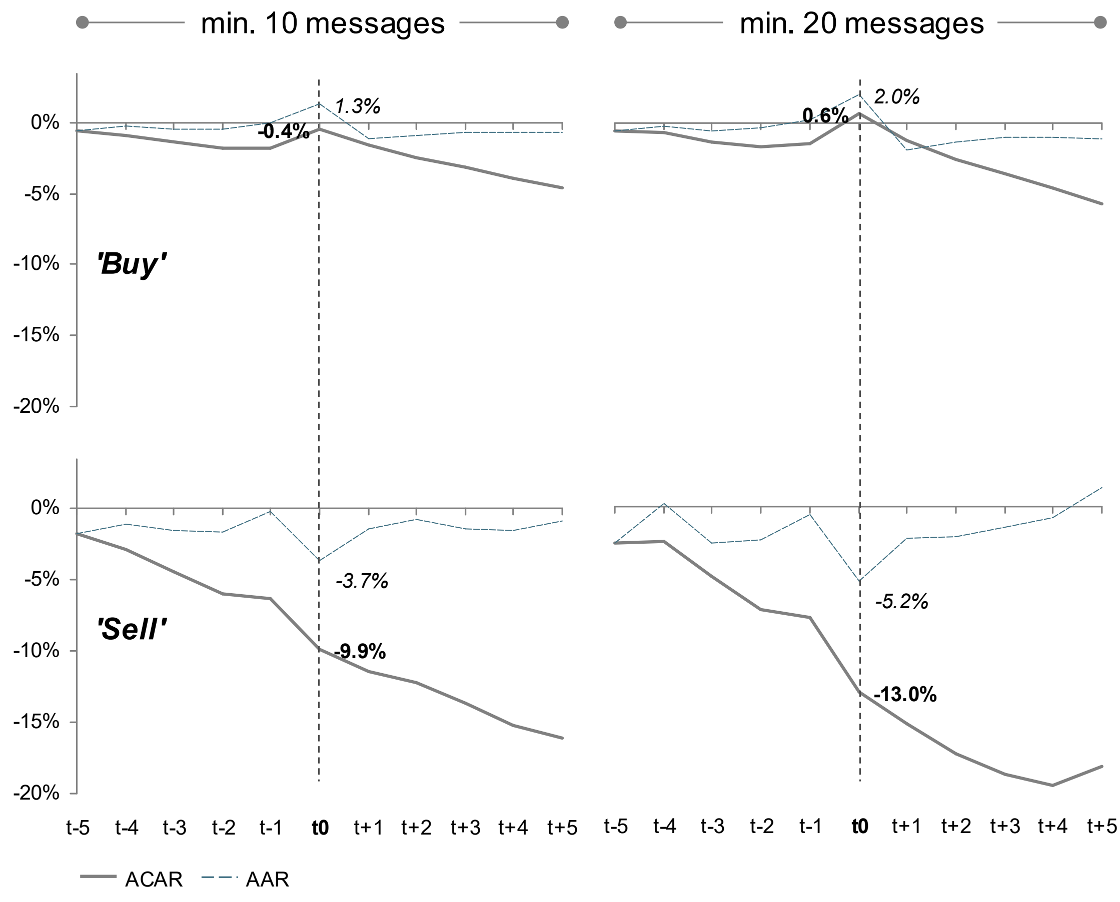

Figure 2. Events with abnormal message board activity (min. 10/20 buy/sell messages)

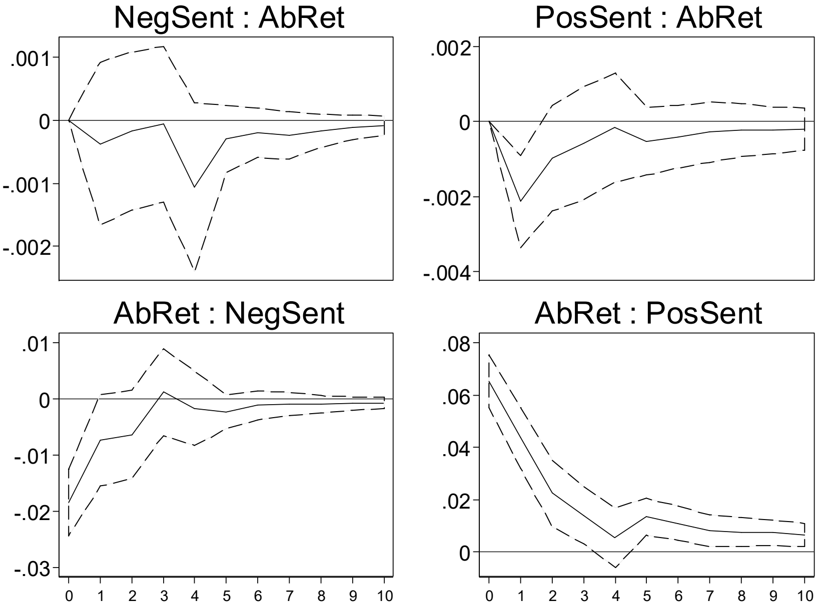

Figure 3. Impulse-response-function for Lag of 3 periods (impulse : response)

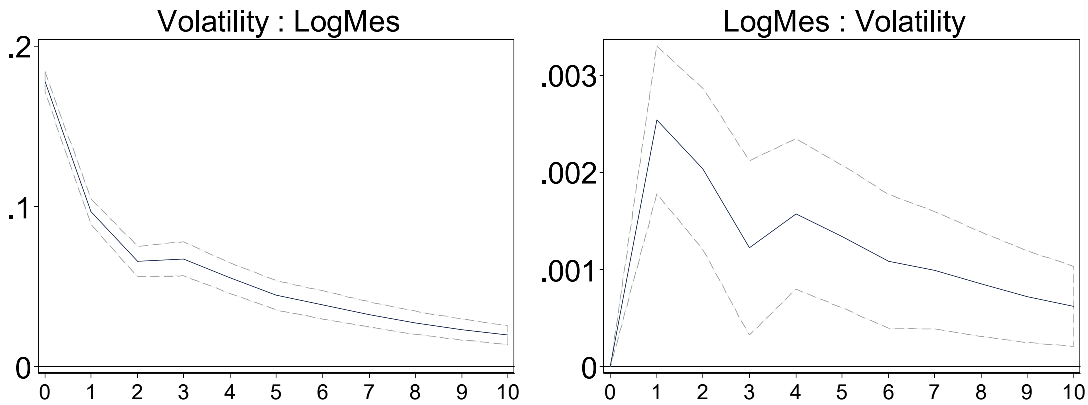

Figure 4. Impulse-response-function for Lag of 3 periods (impulse : response)

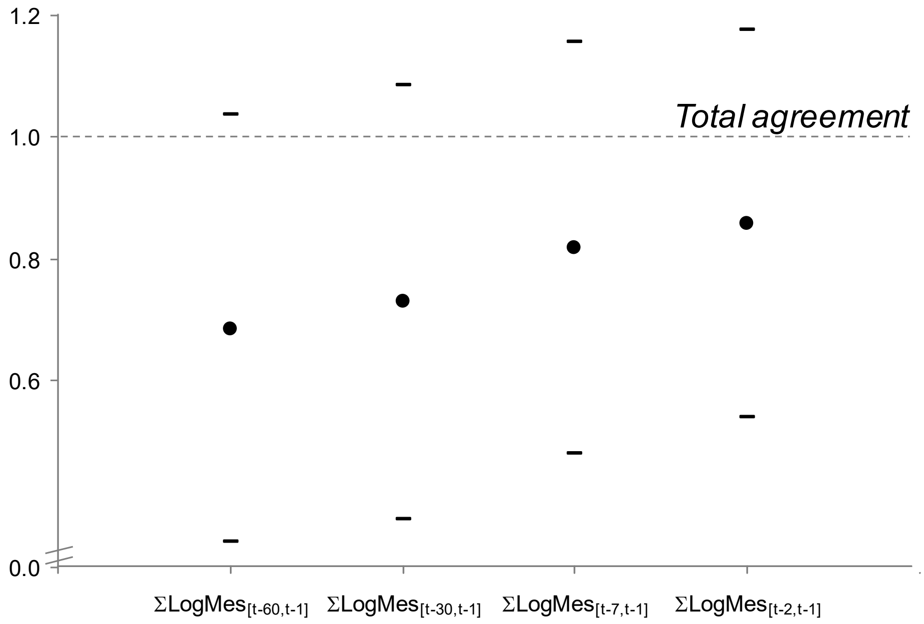

Figure 5. Average cumulated Agreement Index relative to the event date t.

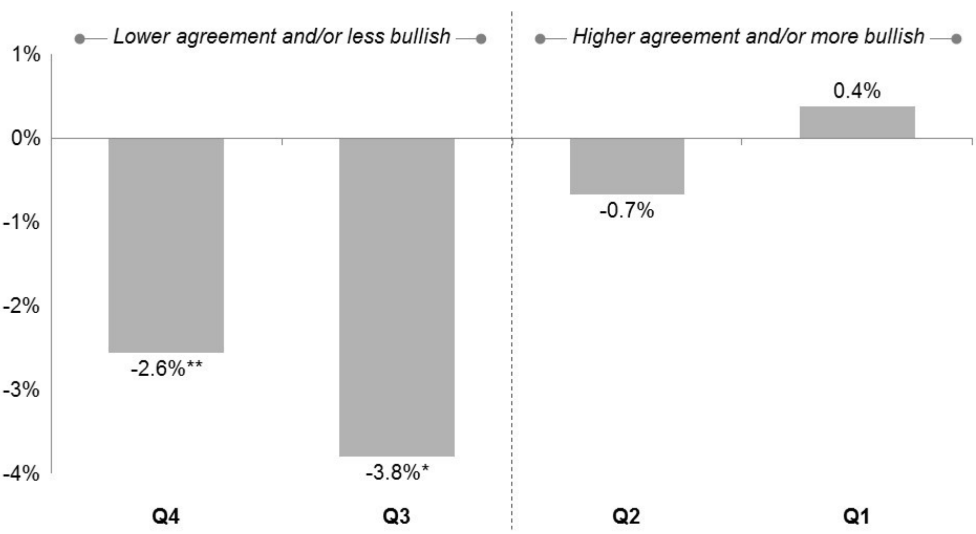

Figure 6. Average unexpected earnings (SUEAF) by sentiment homogeneity quartiles.

The figure presents time-series averages of annual mean values of unexpected earnings based on analyst forecasts, within *sentiment homogeneity* quartiles. The weights are based on the number of messages posted a week before the actual earnings announcement. SUEAF is the difference between the median analyst forecast over the 90-day-period before the announcement and actual earnings divided by the year-end price. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLES

Table 1. Example of HotCopper messages

Ticker	Thread time	Post ID	Posting time	Disclosure	User	Message	Sentiment
EDE	27/04/16 17:13	17615495	28/04/16 07:07	Held	Espinsight	My thoughts are that the Quarterly reports give a neat overview and can contain a clear vision of expectations, particularly for new investors, or those considering investing. Should likely be very positive and confirming.	Buy
EDE	26/04/16 10:41	17598450	26/04/16 12:38	Held	RULES	Plans in place to increase Colorado's capacity to 24,000,000 gals p.a. by late this year to early next year at approx 20% margin on $25.00/gal should pave the way for the cash you reckon is short. Time will Tell.	Buy
EDE	27/04/16 17:13	17618313	28/04/16 11:05	Held	brassmad	As a newbie to HC it's sometimes quite difficult to put together the structure of companies, so your post has helped me in that regard. I'm gradually getting my head around the acronyms but there's one in your post that I can't decipher..... could you let me know what R/I stands for? Really enjoy reading MOST of the comments posted.	Hold
EDE	26/04/16 10:41	17596748	26/04/16 10:41	Not Held	Colstone	The involvement of the state of Georgia as well giving tax breaks and no doubt future business will only benefit this company. But after having a look through their statements in the weekend they have basically no cash at the moment and plans to spend 68mil building a plant that will take years...	Sell

Notes: This table represents four examples of messages posted in the thread 'Quarterly report due this week' on the internet message board HotCopper (https://hotcopper.com.au).

Table 2. Summary statistics: On firm/trading level with 0 days holding period

	N	Mean	Median	Std. Dev.	10^{th} Pctl.	25^{th} Pctl.	75^{th} Pctl.	90^{th} Pctl.
Message board variables								
$LogMessages_{i,t}$	390,842	1.292	1.099	0.703	0.693	0.693	1.609	2.303
$Bullishness_{i,t}$	390,842	1.096	1.099	0.840	0.693	0.693	1.609	2.197
$PosSentiment_{i,t}$	390,842	1.218	1.099	0.733	0.693	0.693	1.609	2.197
$NegSentiment_{i,t}$	390,842	0.136	0.000	0.381	0.000	0.000	0.000	0.693
$Agreement_{i,t}$	390,842	0.925	1.000	0.246	1.000	1.000	1.000	1.000
Financial control variables								
$AbRet_{i,t}$	390,842	-0.001	-0.001	0.070	-0.058	-0.024	0.020	0.059
$AbRet_{i,t-1}$	390,842	-0.003	-0.002	0.067	-0.055	-0.023	0.016	0.049
$AbRet_{i,t-2}$	390,842	-0.002	-0.002	0.068	-0.057	-0.024	0.017	0.052
$Volatility_{i,t-30,t-1}$	390,842	0.047	0.039	0.038	0.017	0.026	0.057	0.083
$Upgrade_{i,t}$	390,842	0.043	0.000	0.412	0.000	0.000	0.000	0.000
$Downgrade_{i,t}$	390,842	0.074	0.000	0.630	0.000	0.000	0.000	0.000
$PosMeanES_{i,t}$	390,842	0.007	0.000	0.083	0.000	0.000	0.000	0.000
$NegMeanES_{i,t}$	390,842	0.002	0.000	0.046	0.000	0.000	0.000	0.000

Notes: This table reports the summary statistics of the main internet message board and financial control variables. The observations are on a firm-day level. $LogMessages_{i,t}$ is the log transformation $(1+M_t)$, $Bullishness_{i,t}$ is the standardized bullishness index defined in formula (1), $PosSentiment_{i,t}$ and $NegSentiment_{i,t}$ describe the positive and negative sentiment denoted in formula (2) and (3), Agreement is the agreement index described in formula (4), $AbRet_{i,t}$ describes the firm's abnormal return, calculated as the difference of compound raw returns and value-weighted market return, $Volatility_{i,t-30,t-1}$ is the 30-day-standard deviation of returns prior to day *t*, $Upgrade_{i,t}$/$Downgrade_{i,t}$ describe the number of analyst upgrade/downgrade recommendation on day *t*, $PosMeanES_{i,t}$/$NegMeanES_{i,t}$ denote dummy variables for positive/negative mean earnings surprise on day *t*.

Table 3. Event study results: Abnormal 'Buy/Sell'-events

Min. of 10 buy messages (n = 13,126)	ACAR (%)	Median CAR (%)	t-test (t-value)	Wilcoxon (Z-Score)
[-1,0]	1.33	0.49	12.33***	11.13***
0	1.33	0.38	15.49***	14.07***
[0,1]	0.22	-0.12	2.21**	0.50
[-5,-1]	-1.77	-1.55	-13.66***	-16.83***
[1,5]	-4.16	-3.27	-33.91***	-36.62***
[-5,5]	-4.59	-3.74	-22.92***	-24.76***
Min. of 20 buy messages (n = 4,247)				
[-1,0]	2.26	0.96	9.59***	9.30***
0	2.03	0.51	10.72***	9.54***
[0,1]	0.16	-0.18	0.74	-0.69
[-5,-1]	-1.40	-1.35	-5.30***	-7.18***
[1,5]	-6.25	-5.16	-26.17***	-27.24***
[-5,5]	-5.61	-4.89	-13.91***	-15.20***
Min. of 10 sell messages (n = 493)				
[-1,0]	-3.89	-3.16	-4.33***	-7.89***
0	-3.65	-1.87	-6.00***	-8.52***
[0,1]	-5.14	-3.27	-7.14***	-8.43***
[-5,-1]	-6.28	-3.86	-5.86***	-7.46***
[1,5]	-6.17	-3.42	-7.02***	-7.68***
[-5,5]	-16.12	-10.89	-10.18***	-10.66***
Min. of 20 sell messages (n = 100)				
[-1,0]	-5.75	-5.78	-2.11**	-3.97***
0	-5.23	-3.13	-2.92***	-4.23***
[0,1]	-7.48	-4.08	-3.89***	-4.15***
[-5,-1]	-7.75	-6.32	-3.02***	-3.98***
[1,5]	-5.28	-3.57	-2.55**	-2.63***
[-5,5]	-18.26	-14.51	-4.59***	-4.84***

Notes: This table describes the average and median cumulative abnormal returns (CAR) for varying event windows surrounding abnormal positive (buy) and negative (sell) posting volume. Significance is tested based on the parametric t-test and the non-parametric Wilcoxon test. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 4. Panel A Regression – All stocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$AbRet_{t0}$	**$AbRet_{t0}$**	**$AbRet_{t0}$**	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+30}$**	**$AbRet_{t0,t+30}$**	**$AbRet_{t0,t+30}$**
$LogMes_{i,t}$	-0.000		-0.002**	-0.008***		-0.012***	-0.010***		-0.012***	-0.018***		-0.021***
	(0.001)		(0.001)	(0.003)		(0.003)	(0.003)		(0.003)	(0.006)		(0.006)
$Bullishness_{i,t}$	0.008***		0.006***	0.019***		0.015***	0.014***		0.012***	0.017***		0.015***
	(0.001)		(0.001)	(0.002)		(0.002)	(0.003)		(0.003)	(0.005)		(0.005)
$PosSentiment_{i,t}$		0.008***			0.012***			0.006***			0.000	
		(0.000)			(0.001)			(0.001)			(0.003)	
$NegSentiment_{i,t}$		-0.010***			-0.028***			-0.026***			-0.032***	
		(0.001)			(0.004)			(0.004)			(0.010)	
$Agreement_{i,t}$	0.008***	0.004***	0.006***	0.008	-0.002	0.001	0.014**	0.003	0.010	0.016**	0.004	0.012
	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.006)	(0.005)	(0.007)	(0.006)	(0.007)	(0.009)	(0.008)
$SentimentHom_{i,t}$			0.003***			0.008***			0.005***			0.005*
			(0.001)			(0.002)			(0.002)			(0.003)
$Vola_{i,t-30,t-1}$	-0.089***	-0.088***	-0.089***	0.311***	0.311***	0.311***	0.600***	0.601***	0.600***	1.569***	1.569***	1.569***
	(0.011)	(0.011)	(0.011)	(0.071)	(0.071)	(0.071)	(0.102)	(0.102)	(0.102)	(0.161)	(0.161)	(0.161)
$LogMes \times Vola_{i,t}$	0.062*	0.063*	0.062*	-0.041	-0.033	-0.037	-0.021	-0.015	-0.019	-0.398***	-0.389***	-0.396***
	(0.033)	(0.033)	(0.033)	(0.048)	(0.047)	(0.048)	(0.105)	(0.105)	(0.105)	(0.103)	(0.103)	(0.103)
$Upgrade_{i,t}$	-0.000	-0.000	-0.000	0.001	0.001	0.001	-0.001	-0.001	-0.001	0.002	0.002	0.002
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$Downgrade_{i,t}$	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003**	-0.003**	-0.003**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$PosMeanES_{i,t}$	-0.003**	-0.003**	-0.003**	-0.000	0.000	-0.000	-0.003	-0.002	-0.003	0.008	0.008	0.008
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
$NegMeanES_{i,t}$	-0.002	-0.002	-0.002	-0.010	-0.010	-0.010	-0.007	-0.007	-0.007	-0.005	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)	(0.017)
$AbRet_{i,t-1}$	0.083***	0.083***	0.084***									
	(0.012)	(0.012)	(0.012)									
$AbRet_{i,t-2}$	-0.000	-0.000	0.000									
	(0.005)	(0.005)	(0.005)									
$AbRet_{i,t-5,t-1}$				-0.115***	-0.116***	-0.115***						
				(0.014)	(0.014)	(0.014)						
$AbRet_{i,t-10,t-1}$							-0.091***	-0.091***	-0.091***			
							(0.013)	(0.013)	(0.013)			
$AbRet_{i,t-30,t-1}$										-0.190***	-0.190***	-0.190***
										(0.017)	(0.017)	(0.017)
Constant	-0.012***	-0.008***	-0.008***	-0.029***	-0.020***	-0.019***	-0.046***	-0.036***	-0.040***	-0.101***	-0.090***	-0.094***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.013)	(0.015)	(0.013)
Observations	390,842	390,842	390,842	362,486	362,486	362,486	354,070	354,070	354,070	303,056	303,056	303,056
Adjusted R-squared	1.7%	1.7%	1.7%	0.6%	0.6%	0.6%	1.2%	1.2%	1.2%	4.7%	4.7%	4.7%

Notes: Firm-fixed regressions were conducted. $LogMessages_{i,t}$ is the log transformation (1+Mt), $Bullishness_{i,t}$ is the standardized bullishness index defined in formula (1), $PosSentiment_{i,t}$ / $NegSentiment_{i,t}$ is the log transformation (1+MtBuy / MtSell), $Agreement_{i,t}$ is the agreement index described in formula (4), $AbRet_{i,t}$ describes the firm's abnormal return, calculated as the difference of compound raw returns and value-weighted market return, $Vola_{i,t-30,t-1}$ is the 30-day-standard deviation of returns prior to day *t*, $Upgrade_{i,t}$/$Downgrade_{i,t}$ describe the number of analyst upgrade/downgrade recommendation on day *t*, $PosMeanES_{i,t}$/$NegMeanES_{i,t}$ denote dummy variables for positive/negative mean earnings surprise on day *t*. T-statistics computed are based on standard errors clustered by firm and year and are denoted in parentheses. ***, **, and * describe significance at 1%, 5% and 10% level, respectively. All stocks are included in these panel regressions.

Table 5. Panel C Regressions – Small stocks

	(1) $AbRet_{t0}$	(2) $AbRet_{t0}$	(3) $AbRet_{t0}$	(4) $AbRet_{t0,t+5}$	(5) $AbRet_{t0,t+5}$	(6) $AbRet_{t0,t+5}$	(7) $AbRet_{t0,t+10}$	(8) $AbRet_{t0,t+10}$	(9) $AbRet_{t0,t+10}$	(10) $AbRet_{t0,t+30}$	(11) $AbRet_{t0,t+30}$	(12) $AbRet_{t0,t+30}$
$LogMes_{i,t}$	-0.000		-0.002*	-0.008***		-0.012***	-0.009**		-0.011**	-0.024***		-0.027***
	(0.001)		(0.001)	(0.003)		(0.003)	(0.004)		(0.005)	(0.006)		(0.007)
$BullInd_{i,t}$	0.009***		0.008***	0.021***		0.018***	0.015***		0.012***	0.020***		0.018***
	(0.001)		(0.001)	(0.002)		(0.003)	(0.004)		(0.004)	(0.006)		(0.006)
$PosSentiment_{i,t}$		0.009***			0.014***			0.006***			-0.002	
		(0.000)			(0.002)			(0.002)			(0.004)	
$NegSentiment_{i,t}$		-0.012***			-0.030***			-0.026***			-0.040***	
		(0.002)			(0.004)			(0.006)			(0.010)	
$AgreeInd_{i,t}$	0.009***	0.006***	0.007***	0.012**	0.002	0.006	0.020***	0.009	0.016**	0.024***	0.010	0.020**
	(0.001)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.007)	(0.008)	(0.010)	(0.009)
$SentimentHom_{i,t}$			0.003***			0.007***			0.005*			0.006*
			(0.001)			(0.002)			(0.002)			(0.003)
$Vola_{i,t-30,t-1}$	-0.078***	-0.077***	-0.078***	0.320***	0.320***	0.320***	0.474***	0.475***	0.474***	1.446***	1.444***	1.446***
	(0.012)	(0.012)	(0.012)	(0.076)	(0.076)	(0.076)	(0.100)	(0.100)	(0.100)	(0.183)	(0.183)	(0.183)
LogMes x $Vola_{i,t}$	0.054	0.055	0.054	-0.022	-0.014	-0.018	0.036	0.043	0.038	-0.363***	-0.352***	-0.361***
	(0.037)	(0.037)	(0.037)	(0.045)	(0.044)	(0.045)	(0.110)	(0.110)	(0.110)	(0.107)	(0.107)	(0.107)
$Upgrade_{i,t}$	-0.000	-0.000	-0.000	-0.003	-0.003	-0.003	-0.007**	-0.007**	-0.007**	0.016	0.016	0.016
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.021)	(0.021)	(0.021)
$Downgrade_{i,t}$	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.006	-0.006	-0.006
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
$PosMeanES_{i,t}$	-0.004	-0.004	-0.004	0.001	0.001	0.001	0.000	0.000	0.000	0.011	0.010	0.011
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)
$NegMeanES_{i,t}$	-0.000	0.000	0.000	-0.009	-0.009	-0.009	-0.004	-0.004	-0.004	-0.015	-0.014	-0.015
	(0.003)	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.022)	(0.022)	(0.022)
$AbRet_{i,t-1}$	0.070***	0.070***	0.070***									
	(0.012)	(0.013)	(0.012)									
$AbRet_{i,t-2}$	0.001	0.001	0.001									
	(0.006)	(0.006)	(0.006)									
$AbRet_{i,t-5,t-1}$				-0.142***	-0.142***	-0.142***						
				(0.015)	(0.015)	(0.015)						
$AbRet_{i,t-10,t-1}$							-0.087***	-0.087***	-0.087***			
							(0.014)	(0.014)	(0.014)			
$AbRet_{i,t-30,t-1}$										-0.193***	-0.193***	-0.193***
										(0.020)	(0.020)	(0.020)
Constant	-0.014***	-0.011***	-0.011***	-0.038***	-0.030***	-0.030***	-0.054***	-0.044***	-0.049***	-0.119***	-0.107***	-0.112***
	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)	(0.011)	(0.015)	(0.016)	(0.016)
Observations	284,452	284,452	284,452	262,641	262,641	262,641	258,553	258,553	258,553	226,332	226,332	226,332
Adjusted R-squared	1.6%	1.6%	1.6%	0.8%	0.9%	0.9%	1.0%	1.1%	1.0%	4.6%	4.6%	4.6%

Notes: Firm-fixed regressions were conducted. $LogMessages_{i,t}$ is the log transformation (1+Mt), $Bullishness_{i,t}$ is the standardized bullishness index defined in formula (1), $PosSentiment_{i,t}$ / $NegSentiment_{i,t}$ is the log transformation (1+MtBuy / MtSell), $Agreement_{i,t}$ is the agreement index described in formula (4), $AbRet_{i,t}$ describes the firm's abnormal return, calculated as the difference of compound raw returns and value-weighted market return, $Vola_{i,t-30,t-1}$ is the 30-day-standard deviation of returns prior to day *t*, $Upgrade_{i,t}$/$Downgrade_{i,t}$ describe the number of analyst upgrade/downgrade recommendation on day *t*, $PosMeanES_{i,t}$/$NegMeanES_{i,t}$ denote dummy variables for positive/negative mean earnings surprise on day *t*. T-statistics computed are based on standard errors clustered by firm and year and are denoted in parentheses. ***, **, and * describe significance at 1%, 5% and 10% level, respectively. Only small capitalization stocks are included in these panel regressions.

Table 6. Lag-order selection statistics for VAR – Aggregate level

Lag	Likelihood-Ratio	DoF	p-Value	FPE	AIC	HQIC	SBIC
0				0.000	-11.719	-11.707	-11.688
1	791.334	9	0.000	0.000	-13.755	-13.705	-13.630
2	82.153	9	0.000	0.000	-13.923	-13.837	-13.706*
3	49.629	9	0.000	0.000	-14.007	-13.883*	-13.696
4	20.092*	9	0.017	0.000*	-14.012*	-13.852	-13.608

Notes: * indicates the lag order selected by each criterion, where FPE = Final prediction error, AIC = Akaike information criterion, SBIC = Schwarz information criterion and HQIC = Hannan-Quinn information criterion

Table 7. VAR on abnormal returns and message board sentiment (aggregate level)

Lags	*2* **$Abret_t$**	*4 (opt.)* **$Abret_t$**	*2* **$PosSent_t$**	*4 (opt.)* **$PosSent_t$**	*2* **$NegSent_t$**	*4 (opt.)* **$NegSent_t$**
Intercept	0.009**	0.013*	0.090***	0.040	0.008	0.006
	(2.477)	(1.931)	(5.225)	(1.394)	(0.829)	(0.373)
$Abret_{t-1}$	0.031	-0.067	0.181	0.247	-0.172**	-0.115
	(1.108)	(-1.297)	(1.436)	(1.148)	(-2.483)	(-0.900)
$Abret_{t-2}$	0.022	-0.020	0.028	0.064	0.050	-0.102
	(0.852)	(-0.392)	(0.234)	(0.310)	(0.761)	(-0.828)
$Abret_{t-3}$		0.012		0.062		-0.147
		(0.261)		(0.318)		(-1.256)
$Abret_{t-4}$		-0.014		0.195		-0.104
		(-0.308)		(1.064)		(-0.953)
$PosSent_{t-1}$	-0.005	-0.007	0.602***	0.407***	0.015	-0.019
	(-0.918)	(-0.575)	(22.458)	(7.868)	(0.992)	(-0.627)
$PosSent_{t-2}$	0.006	0.006	0.309***	0.240***	0.009	-0.026
	(1.076)	(0.454)	(11.565)	(4.488)	(0.621)	(-0.818)
$PosSent_{t-3}$		0.009		0.115**		0.048
		(0.716)		(2.262)		(1.572)
$PosSent_{t-4}$		-0.005		0.186***		0.022
		(-0.397)		(3.889)		(0.771)
$NegSent_{t-1}$	-0.063***	-0.065***	0.101**	-0.081	0.518***	0.435***
	(-5.763)	(-3.117)	(2.029)	(-0.943)	(18.897)	(8.433)
$NegSent_{t-2}$	-0.001	-0.008	0.002	0.222**	0.236***	0.052
	(-0.083)	(-0.344)	(0.046)	(2.377)	(8.597)	(0.925)
$NegSent_{t-3}$		-0.013		-0.075		0.209***
		(-0.584)		(-0.804)		(3.719)
$NegSent_{t-4}$		-0.008		0.015		0.059
		(-0.392)		(0.183)		(1.206)
Observations	1,230	380	1,230	380	1,230	380
χ^2-stat *AbRet*			2.224	3.201	6.393	5.177
p-Value *AbRet*			0.329	0.525	0.041**	0.270
χ^2-stat *PSent.*	1.159	1.091				
p-Value *PSent.*	0.560	0.896				
χ^2-stat *NSent.*	60.352	33.191				
p-Value *NSent.*	0.000***	0.000***				

Notes: The observations are on an aggregate level. $Abret_t$ is the average difference of value-weighted market and stock return, $PosSentiment_t$ / $NegSentiment_t$ is the log transformation of (1 + M_t^{Buy} / M_t^{Sell}). Z-statistics are reported in parenthesis. χ^2-test statistics are shown for the exclusion of the individual variable for the Granger-causality Wald-test. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 8. Panel VAR on abnormal returns and message board sentiment (individual level)

	(1) AbRet$_t$	(2) opt. AbRet$_t$	(3) AbRet$_t$	(4) PosSent$_t$	(5) opt. PosSent$_t$	(6) PosSent$_t$	(7) NegSent$_t$	(8) opt. NegSent$_t$	(9) NegSent$_t$
AbRet$_{t-1}$	-0.034***	-0.036***	-0.025	0.172***	0.301***	0.352***	0.020	0.024	-0.035
	(-3.988)	(-2.754)	(-1.526)	(4.846)	(5.630)	(3.595)	(0.804)	(0.622)	(-0.477)
AbRet$_{t-2}$	-0.019***	-0.018*	-0.025	-0.215***	-0.048	-0.066	0.044**	0.068**	-0.036
	(-2.840)	(-1.753)	(-1.186)	(-6.637)	(-0.891)	(-0.659)	(2.086)	(2.027)	(-0.554)
AbRet$_{t-3}$		0.009	0.046***		-0.212***	-0.156		0.009	0.110*
		(0.932)	(3.364)		(-4.199)	(-1.611)		(0.307)	(1.773)
AbRet$_{t-4}$			-0.020*			-0.340***			0.028
			(-1.667)			(-3.669)			(0.541)
PosSent$_{t-1}$	-0.001	-0.002**	-0.003***	0.442***	0.404***	0.367***	-0.007**	-0.001	0.004
	(-1.207)	(-2.294)	(-2.998)	(86.134)	(58.193)	(32.002)	(-2.251)	(-0.295)	(0.528)
PosSent$_{t-2}$	0.001***	0.000	-0.000	0.249***	0.196***	0.167***	-0.019***	-0.010***	-0.003
	(2.912)	(0.788)	(-0.345)	(52.833)	(30.531)	(15.095)	(-7.201)	(-2.720)	(-0.493)
PosSent$_{t-3}$		0.001**	0.000		0.163***	0.125***		-0.008**	-0.011*
		(1.998)	(0.107)		(25.949)	(11.697)		(-2.109)	(-1.954)
PosSent$_{t-4}$			0.001			0.136***			-0.007
			(1.184)			(13.100)			(-1.241)
NegSent$_{t-1}$	-0.003***	-0.001	-0.001	0.031***	0.041***	0.044**	0.340***	0.318***	0.301***
	(-3.414)	(-1.147)	(-0.598)	(4.260)	(4.036)	(2.541)	(49.809)	(33.665)	(19.418)
NegSent$_{t-2}$	-0.001	-0.000	-0.000	-0.018**	-0.013	-0.016	0.170***	0.129***	0.110***
	(-1.042)	(-0.084)	(-0.030)	(-2.553)	(-1.309)	(-0.912)	(26.552)	(14.811)	(7.508)
NegSent$_{t-3}$		-0.001	0.000		-0.014	-0.001		0.107***	0.096***
		(-1.180)	(0.041)		(-1.448)	(-0.047)		(11.977)	(6.301)
NegSent$_{t-4}$			-0.003			-0.028			0.059***
			(-1.566)			(-1.628)			(4.059)
Observations	90,503	42,872	15,039	90,503	42,872	15,039	90,503	42,872	15,039
χ^2-stat *AbRet*				73.106	52.271	29.567	4.735	4.286	3.744
p-Value *AbRet*				0.000***	0.000***	0.000***	0.094*	0.232	0.442
χ^2-stat *PosSent*	11.991	12.919	12.582						
p-Value *PosSent*	0.002***	0.005***	0.014**						
χ^2-stat *NegSent*	13.974	2.800	2.736						
p-Value *NegSent*	0.001***	0.423	0.603						

Notes: The observations are on individual stock level. *Abret$_t$* is the difference of value-weighted market and stock return, *PosSentiment$_t$* / *NegSentiment$_t$* is the log transformation of (1 + M_t^{Buy} / M_t^{Sell})Z-statistics are reported in parenthesis. χ^2-test statistics are shown for the exclusion of the individual variable for the Granger-causality Wald-test. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 9. Shortselling and sentiment regressions

	Panel A: All observations				*Panel B: Min. 10 messages on day t*				*Panel C: Min. 20 messages on day t*			
	$AbRet_{t0}$	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+30}$**	**$AbRet_{t0}$**	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+30}$**	**$AbRet_{t0}$**	**$AbRet_{t0,t+5}$**	**$AbRet_{t0,t+10}$**	**$AbRet_{t0,t+30}$**
$PosSentiment_{i,t}$	0.008***	0.011***	0.004**	-0.002	0.022***	0.022***	0.003	0.004	0.037***	0.042***	0.014	0.027*
	(0.000)	(0.001)	(0.002)	(0.004)	(0.002)	(0.005)	(0.005)	(0.010)	(0.005)	(0.012)	(0.011)	(0.015)
$NegSentiment_{i,t}$	-0.012***	-0.029***	-0.024***	-0.034***	-0.023***	-0.040***	-0.046***	-0.066*	-0.023***	-0.041**	-0.046**	-0.060**
	(0.001)	(0.005)	(0.005)	(0.011)	(0.004)	(0.010)	(0.013)	(0.037)	(0.008)	(0.020)	(0.020)	(0.030)
$AgreeInd_{i,t}$	0.003**	-0.006	0.004	0.003	-0.002	-0.024	-0.033	-0.059	0.010	-0.020	-0.036	-0.095
	(0.001)	(0.007)	(0.007)	(0.010)	(0.008)	(0.018)	(0.026)	(0.064)	(0.020)	(0.043)	(0.053)	(0.074)
$PercShort_{i,t}$	0.001***	-0.000	-0.003***	-0.008***	0.005***	-0.000	-0.012**	-0.014	0.023***	0.028**	-0.019	-0.010
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)	(0.010)	(0.005)	(0.012)	(0.028)	(0.022)
PosSent x $PercShort_{i,t}$	-0.001***	-0.000	0.001***	0.003***	-0.002***	-0.001	0.003*	0.002	-0.007***	-0.010***	0.003	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.007)	(0.005)
NegSent x $PercShort_{i,t}$	0.001***	-0.000	0.000	0.001	0.001***	0.000	-0.000	0.001	0.002***	0.000	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Other Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm-Year-clustered SE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	329,308	305,317	299,276	258,223	30,683	28,637	27,878	22,535	9,894	9,089	8,748	6,722
Adjusted R-squared	1.7%	0.6%	1.3%	4.5%	3.6%	0.9%	1.4%	5.5%	5.4%	2.4%	3.9%	3.0%
F-value	73.07	20.09	15.36	15.76	33.12	11.24	9.066	8.342	19.21	10.02	6.724	4.272

Notes: $PosSentiment_{i,t}$ / $NegSentiment_{i,t}$ is the log transformation (1+MtBuy / MtSell), $Agreement_{i,t}$ is the agreement index described in formula (4), $AbRet_{i,t}$ describes the firm's abnormal return, calculated as the difference of compound raw returns and value-weighted market return, $PercShort_{i,t}$ denotes the share of reported short positions of total shares outstanding, *Other Controls* include all other control variables and interaction terms of former regressions. T-statistics computed are based on standard errors clustered by firm and year and are denoted in parentheses. ***, **, and * describe significance at 1%, 5% and 10% level, respectively

Table 10. Regressions on volatility

	$Vola_{i,t}$	$Vola_{i,t+1}$	$Vola_{i,t+1,t+5}$	$Vola_{i,t+1,t+10}$	$Vola_{i,t+1,t+30}$
$LogMessages_{i,t}$	0.033***	0.022***	0.009***	0.008***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
$Bullishness_{i,t}$	-0.005***	-0.005***	-0.004***	-0.004***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
$Agreement_{i,t}$	-0.000	0.003	0.004*	0.004*	0.005***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
$MarketRet_t$	-0.070**	-0.141***	-0.063	-0.087**	-0.047*
	(0.034)	(0.043)	(0.044)	(0.041)	(0.028)
Constant	0.032***	0.040***	0.037***	0.043***	0.046***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	671,029	670,304	822,288	853,854	860,192
Adjusted R-squared	3.91%	1.73%	0.41%	0.34%	0.35%

Notes: The observations are on a firm-day level. $LogMessages_{i,t}$ is the log transformation $(1+M_t)$, $Bullishness_{i,t}$ is the standardized bullishness index defined in formula (1), Agreement is the agreement index described in formula (4), $MarketRet_{i,t}$ describes the All Ordinaries market return, $Vola_{i,t}$ and $Vola_{i,t+1}$ are the intraday price volatility, $Vola_{i,t+1,t+5/10/30}$ is the standard deviation of return in the respective time window. Robust standard errors are denoted in parenthesis. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 11. Lag-order selection statistics for VAR – Aggregate level

Lag	Likelihood-Ratio	DoF	p-Value	FPE	AIC	HQIC	SBIC
0	0.0000			0.0000	-6.5294	-6.5211	-6.5086
1	924.8699	4	0.0000	0.0000	-8.9422	-8.9175	-8.8800
2	68.6352	4	0.0000	0.0000	-9.1017	-9.0606	-8.9981
3	26.4214*	4	0.0000	0.0000	-9.1502	-9.0926*	-9.0051*
4	8.4347	4	0.0769	0.0000*	-9.1514*	-9.0773	-8.9647

Notes: * indicates the lag order selected by each criterion, where FPE = Final prediction error, AIC = Akaike information criterion, SBIC = Schwarz information criterion and HQIC = Hannan-Quinn information criterion

Table 12. VAR on stock price volatility and message board activity (aggregate level)

Explanatory variable	$Vola_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j}, Vola_{t-j} + \sum_{j=1}^{L} \gamma_{1,j}, LogMes_{t-j} + \varepsilon_{1t}$			$LogMes_t = \alpha_1 + \sum_{j=1}^{L} \beta_{2,j}, Vola_{t-j} + \sum_{j=1}^{L} \gamma_{2,j}, LogMes_{t-j} + \varepsilon_{1t}$		
Lags	*2*	*3 (opt)*	*4*	*2*	*3 (opt.)*	*4*
	$Vola_t$	**$Vola_t$**	**$Vola_t$**	**$LogMes_t$**	**$LogMes_t$**	**$LogMes_t$**
Intercept	0.014***	0.011***	0.008*	0.133***	0.118***	0.082*
	(6.308)	(3.995)	(1.812)	(5.869)	(4.240)	(1.957)
$LogMes_{t-1}$	0.002	0.002	-0.005	0.661***	0.590***	0.521***
	(0.844)	(0.599)	(-0.801)	(24.693)	(16.500)	(8.952)
$LogMes_{t-2}$	-0.003	-0.003	-0.000	0.267***	0.180***	0.119**
	(-1.119)	(-0.867)	(-0.022)	(10.035)	(4.732)	(2.003)
$LogMes_{t-3}$		-0.001	-0.002		0.168***	0.208***
		(-0.348)	(-0.352)		(5.187)	(3.798)
$LogMes_{t-4}$			0.004			0.097**
			(0.717)			(2.082)
$Vola_{t-1}$	0.482***	0.454***	0.561***	-0.809***	-0.855**	-0.006
	(19.136)	(11.704)	(9.076)	(-3.131)	(-2.265)	(-0.010)
$Vola_{t-2}$	0.312***	0.287***	0.335***	0.524**	0.555	0.386
	(12.642)	(8.224)	(5.144)	(2.072)	(1.636)	(0.641)
$Vola_{t-3}$		0.135***	0.027		-0.053	0.403
		(4.293)	(0.532)		(-0.174)	(0.858)
$Vola_{t-4}$			0.050			-0.876*
			(0.953)			(-1.817)
Observations	1,230	797	380	1,230	797	380
χ^2-stat	1.361	2.978	3.271	9.823	6.416	3.863
p-Value	0.506	0.395	0.513	0.007	0.093	0.425

Notes: The observations are on an aggregate level. *$Vola_{tt}$* is the scaled difference of the lowest and highest stock price and *$LogMes_t$* is the log transformation $(1+M_t)$. Z-statistics are reported in parenthesis. χ^2-test statistics are shown for the exclusion of the individual variable for the Granger-causality Wald-test. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 13. Panel VAR on stock price volatility and message board activity (individual level)

Explanatory variable	$Vola_t = \alpha_{i,1} + \sum_{j=1}^{L} \beta_{1,j} Vola_{i,t-j} + \sum_{j=1}^{L} \gamma_{1,j} LogMes_{i,t-j} + \varepsilon_{1t}$			$LogMes_t = \alpha_{i,1} + \sum_{j=1}^{L} \beta_{2,j} Vola_{i,t-j} + \sum_{j=1}^{L} \gamma_{2,j} LogMes_{o,t-j} + \varepsilon_{1t}$		
Lags	*2*	*3 (opt.)*	*4*	*2*	*3 (opt.)*	*4*
	$Vola_t$	**$Vola_t$**	**$Vola_t$**	**$LogMes_t$**	**$LogMes_t$**	**$LogMes_t$**
$LogMes_{t-1}$	0.004***	0.004***	0.004***	0.430***	0.398***	0.369***
	(9.176)	(6.809)	(4.373)	(80.483)	(56.013)	(32.134)
$LogMes_{t-2}$	-0.000	0.001	0.001	0.244***	0.192***	0.163***
	(-0.134)	(1.175)	(1.557)	(48.998)	(28.975)	(14.461)
$LogMes_{t-3}$		-0.001	0.000		0.163***	0.128***
		(-1.455)	(0.528)		(24.717)	(11.671)
$LogMes_{t-4}$			0.001			0.124***
			(0.895)			(11.389)
$Vola_{t-1}$	0.237***	0.239***	0.232***	0.426***	0.483***	0.361***
	(25.306)	(16.604)	(11.132)	(9.479)	(6.851)	(2.807)
$Vola_{t-2}$	0.097***	0.075***	0.058***	-0.216***	-0.249***	-0.251*
	(12.020)	(6.131)	(2.798)	(-5.617)	(-3.858)	(-1.958)
$Vola_{t-3}$		0.088***	0.081***		-0.124**	-0.223*
		(7.923)	(4.690)		(-2.078)	(-1.956)
$Vola_{t-4}$			0.070***			0.004
			(3.591)			(0.040)
Observations	90,503	42,872	15,039	90,503	42,872	15,039
χ^2-stat	86.244	51.632	22.645	115.499	66.607	15.218
p-Value	0.000	0.000	0.000	0.000	0.000	0.004

Notes: The observations are on individual stock level. *$Vola_t$* is the scaled difference of the lowest and highest stock price and *$LogMes_t$* is the log transformation $(1+M_t)$. Z-statistics are reported in parenthesis. χ^2-test statistics are shown for the exclusion of the individual variable for the Granger-causality Wald-test. ***, **, and * describe significance at 1%, 5% and 10%-levels, respectively.

Table 14. Summary statistics for panel B: HotCopper

VARIABLES	N	Mean	Median	Std. Dev.	10^{th} Pctl.	25^{th} Pctl.	75^{th} Pctl.	90^{th} Pctl.
$SUEAF_{i,t}$	479	-0.014	-0.001	0.186	-0.090	-0.013	0.009	0.052
$LogMessages_{i,7}$	479	2.147	2.079	1.038	0.693	1.386	2.944	3.555
$Bullishness_{i,7}$	479	1.784	1.791	1.196	0.649	1.075	2.565	3.359
$Agreement_{i,7}$	479	0.817	1.000	0.338	0.169	1.000	1.000	1.000
$Return_{i,50}$	479	-0.027	-0.020	0.352	-0.362	-0.174	0.120	0.304
$Return_{i,5}$	479	-0.003	0.000	0.083	-0.099	-0.042	0.040	0.092
$LogTurnover_{i,50}$	479	13.840	13.510	2.081	11.330	12.260	15.360	16.810
$Volatility_{i,10}$	479	0.029	0.025	0.017	0.012	0.017	0.036	0.051
$LogSize_{i,t}$	479	24.430	24.110	1.721	22.530	23.310	25.430	26.970

Notes: This table reports the summary statistics for the main regression surrounding annual earnings announcements. $SUEAF_{i,t}$ is the difference in actual EPS and forecasted EPS using analyst forecasts 90 days prior to the earnings announcement date scaled by the stock price of the end of the year, $LogMessages_{i,7}$ is the log transformation of (1 + M_t) for the event window [-7,-1], $Bullishness_{i,7}$ is the cumulated bullishness index using formula (3), $Agreement_{i,7}$ is the cumulated agreement index using formula (4), $Return_{i,50}$ is the compounded return over the period of [-61,-12] and $Return_{i,5}$ for the five-day return period [-6,-2] prior to the earnings announcement date. $LogTurnover_{i,50}$ is the log-transformed average turnover over the time window [-61,-12] prior to the earnings announcement date, $Volatility_{i,10}$ is the standard deviation of daily returns in the time window [-11,-2] and $LogSize_{i,t}$ is the log-transformation of the market capitalization at the end of the financial year.

Table 15. Message board activity as predictor of Earnings Surprise

	(1) $SUEAF_{t0}$	(3) $SUEAF_{t0}$	(1) $SUEHIST_{t0}$	(3) $SUEHIST_{t0}$
$LogMessages_{i,7}$	0.019	-0.012	-0.597	-0.551*
	(0.013)	(0.014)	(0.368)	(0.329)
$Bullishness_{i,7}$	-0.022*	-0.061***	0.402	0.445
	(0.012)	(0.018)	(0.344)	(0.396)
$Agreement_{i,7}$	0.060**	-0.045	-0.543	-0.405
	(0.026)	(0.029)	(0.651)	(0.540)
$SentimentHom_{i,7}$		0.082***		-0.105
		(0.020)		(0.204)
$Return_{50}$	-0.057**	-0.070***	-0.374	-0.362
	(0.024)	(0.024)	(0.286)	(0.302)
$Return_{5}$	0.539**	0.522**	1.867**	1.897**
	(0.228)	(0.206)	(0.744)	(0.773)
$LogTurnover_{50}$	0.013	0.024	-0.194	-0.209
	(0.020)	(0.020)	(0.205)	(0.217)
$Volatility_{i,10}$	-2.158**	-1.978**	12.003	11.808
	(0.945)	(0.884)	(9.286)	(9.311)
$LogSize_{i,t}$	0.002	-0.008	0.335*	0.351*
	(0.021)	(0.020)	(0.178)	(0.190)
Constant	-0.227	-0.016	-4.974***	-5.312***
	(0.377)	(0.357)	(1.743)	(1.904)
Observations	479	479	560	560
Adjusted R-squared	14.6%	22.0%	10.0%	10.0%

Notes: Firm-fixed regressions were conducted. Standard errors are clustered by firm and year and are denoted in parentheses. $SUEAF_{i,t}$ is the difference in actual EPS and forecasted EPS using analyst forecasts 90 days prior to the earnings announcement date scaled by the stock price of the end of the year, $SUEHIST_{i,t}$ is the difference in actual EPS in year *t* and the previous year actual EPS scaled by the stock price of the end of the year, $LogMessages_{i,7}$ is the log transformation of $(1 + M_t)$ for the event window [-7,-1], $Bullishness_{i,7}$ is the cumulated bullishness index using formula (3), $Agreement_{i,7}$ is the cumulated agreement index using formula (4), $SentimentHom_{i,7}$ is the interaction term $Bullishness_{i,t}$ x $Agreement_{i,t}$, $Return_{50}$ is the compounded return over the period of [-61,-12] and $Return_5$ for the five-day return period [-6,-2] prior to the earnings announcement date. $LogTurnover_{50}$ is the log-transformed average turnover over the time window [*-61,-12*] prior to the earnings announcement date, $Volatility_{i,10}$ is the standard deviation of daily returns in the time window [*-11,-2*] and $LogSize_{i,t}$ is the log-transformation of the market capitalization at the end of the financial year. ***, **, and * describe significance at 1%, 5% and 10% level, respectively.