# DIFFERENTIAL EMOTIONS AND THE STOCK MARKET. THE CASE OF COMPANY-SPECIFIC TRADING.

*Completed Research*

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## Abstract

*Practitioners and researchers alike increasingly use social media messages as an additional source of information to analyse stock price movements. In this regard, previous preliminary findings demonstrate the incremental value of considering the multi-dimensional structure of human emotions in sentiment analysis instead of the predominant assessment of the binary positive-negative valence of emotions. Therefore, based on emotion theory and an established sentiment lexicon, we develop and apply an open source dictionary for the analysis of seven different emotions (affection, happiness, satisfaction, fear, anger, depression, and contempt).To investigate the connection between the differential emotions and stock movements we analyse approximately 5.5 million Twitter messages on 33 S&P 100 companies and their respective NYSE stock prices from Yahoo!Finance over a period of three months. Subsequently, we conduct a lagged fixed-effects panel regression on the daily closing value differences. The results generally support the assumption of the necessity of considering a more differentiated sentiment. Moreover, comparing positive and negative valence, we find that only the average negative emotionality strength has a significant connection with company-specific stock price movements. The emotion specific analysis reveals that an increase in depression and happiness strength is associated with a significant decrease in company-specific stock prices.*

*Keywords: Differential Emotions; Sentiment Analysis; Stock Price Movements; Twitter.*

## 1    Introduction

Comprehensive and immediate information plays a crucial role in stock price analysis. In this regard, researchers and practitioners alike increasingly consider online user-generated content as an additional source of information for investment decision-making. Events like the loss of approximately 136 billion US-dollars in equity market value within three minutes due to a fake tweet from the hacked Associated Press Twitter account (Moore and Roberts, 2013) demonstrate the interwovenness between social media and stock markets. Social media also affects the stock market on a more regular basis, seeing that the New York Stock Exchange introduced an automated sentiment analysis of social media platforms to provide investors with real-time information on indices, industry sectors or specific companies (NYSE, 2014).

In this regard, research has begun to investigate the impact of different social media activities such as message volume (e.g., Antweiler and Frank, 2004) or joint company mentions (Sprenger and Welpe, 2011) on market indices and company stocks. With the advancement of respective research methods, the social mood in terms of social media sentiment has increasingly moved into focus (Luo et al., 2013). Company-specific tweet sentiments intervene with investor decision making (Li et al. 2014) and affect market prices through information leakage (Sprenger et al., 2014a). Recently, researchers found differential effects for positive and negative messages on stock prices (Sprenger et al., 2014a) and an improvement of the predictive validity on global market indices by considering of specific emotions (e.g., Smailović et al., 2013) while the undifferentiated sentiment shows a poorer correlation with company stocks (Das and Chen, 2007). In this vein, Bollen et al. (2011) considered separate emotions and were able to find a correlation between calmness and a market index.

So far, however, the majority of research has ignored the more complex, multi-dimensional structure of human emotions and only considered aggregated sentiment measures or made binary distinctions between positive and negative sentiment (e.g., Li et al., 2014; Sprenger et al., 2014a; Sprenger et al., 2014b). So far, the few studies that have assessed differentiated emotions are limited to general market indices (Gilbert and Karahalios, 2010; Mittal and Goel, 2012), included very few emotion words (Zhang et al., 2011), has neglected the predictive value of specific emotions (Porshnev et al., 2013) and withheld specifics on the operationalization of the emotions (Bollen et al., 2011). Existent sentiment tools that analyse differential emotions do neither consider the strength of the emotions (Porshnev et al., 2013) nor the exclusiveness of emotional states (Baccianella et al., 2010).

In this study, we address this research gap by developing an open source emotion-specific dictionary which is derived from the established SentiStrength word list and enables us to measure the emotion strength (Thelwall et al., 2012)[1]. We assess seven different emotions whose operationalization is based on the descriptions of the model of the hierarchical structure of the affective domain of Ekkekakis (2013). Subsequently, this sentiment analysis is applied to 5.5 million Twitter messages on 33 S&P 100 companies which we collected over a three-month period. Ultimately, we conduct a lagged panel regression of the differentiated emotion strength on the company-specific NYSE stock price movements obtained from Yahoo!Finance. Thereby, we address calls for IS research regarding a more effective methodology to quantitatively analyse the impact of social media information on stock markets (Li et al., 2014) and a more comprehensive understanding of influences on stock market reactions (Tetlock, 2007). Overall, in this study we investigate *how differential emotions correspond to company-specific stock price movements*.

The remainder of this paper is organized as follows. In the next section, we elaborate the theoretical background of differentiated emotions and research on the association with stock prices. Subsequently, we provide details of our empirical research approach and the results. Ultimately, we discuss the findings in the light of the study's limitations and present its implications for further research.

# 2 Theoretical Background

## 2.1 Sentiment analysis and stock price movements

Regarding the prediction of stock movements, early theories like the well-known efficient market hypothesis and random walk theory claim that investors build their expectations rationally and that stock prices fully reflect every relevant piece of information (Fama, 1970). However, research from emotion psychology, decision-making, and behavioural finance contradict this assumption by providing substantial insights regarding the effect of investor mood on equity pricing (Dowling and Lucey, 2008).

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[1] We provide open access to the differentiated sentiment lexicon with the emotion specific coding here: http://bit.ly/1BpocLl

The impact of emotions on stock prices has been related, for example, to their effect on rational thinking and behaviour (Smailović et al., 2014), misattributions of perceptions (Nofsinger, 2005), judgments of risk, decision-making, and task performance (Boyle et al. 2004). Especially the collective mood of the people around investors and the society (also referred to as "social mood" (Prechter, 2002)) has been found to govern the character of financial and economic activities (Luo et al., 2013). Given the short response times of stock markets compared to other business activities, stock movements are a valid correspondence of social mood (Nofsinger, 2005). Considering that the public mood spreads through social interactions, the analysis of the general social mood can be used to predict stock prices (Smailović et al., 2014). In this regard, social media provides readers with real-time access to public opinions, feelings, and comments. A major stream of research has investigated the value of undifferentiated sentiment of user-generated content on stock movements (see figure 1). Accordingly, company-specific sentiments of Twitter messages have been found to intervene with investor decision making (Li et al. 2014), affect market prices through information leakage (Sprenger et al., 2014a), has predictive power for daily stock price changes (Smailović et al., 2014; Sprenger et al., 2014b; Zhang et al., 2011) apart from information on previous shifts in stock indicators (Porshnev et al. 2013). Recently, research has begun to investigate the differentiated sentiment of user-generated content, as Sprenger et al. (2014a) found separate effects of positive and negative messages. In this vein, considering different emotions has been found to improve the explanatory power of sentiments on global market indices (e.g., Porshnev et al., 2013; Smailović et al., 2013) which could be ascribed to the specific emotion of calmness (Bollen et al., 2011). However, it remains unclear how these emotions were operationalized and whether differentiated emotions have incremental explanatory power in the company-specific context. Thus, we address this research gap by developing a differentiated sentiment analysis, based on an open source dictionary (Thelwall et al., 2012) and an established emotion model (Ekkekakis, 2013) to analyse company-specific tweets and their relation to stock prices.

| | | | |
|---|---|---|---|
| **STOCK MARKET VARIABLES** — Company Stocks | Antweiler and Frank (2004)<br>Das and Chen (2007)<br>Sehgal and Song (2007)<br>Oh and Sheng (2011)<br>Tirunillai and Tellis (2012) | Luo et al. (2013)<br>Nann et al. (2013)<br>Yu et al. (2013)<br>Li et al. (2014)<br>Smailović et al. (2014)<br>Sprenger et al. (2014a)<br>Sprenger et al. (2014b) | **RESEARCH GAP** |
| **STOCK MARKET VARIABLES** — Market Indices | | Das and Chen (2007)<br>Xu et al. (2012) | Gilbert and Karahalios (2010)<br>Bollen et al. (2011)<br>Mittal and Goel (2011)<br>Zhang et al. (2011)<br>Porshnev et al. (2013) |
| | undifferentiated | SENTIMENT VARIABLES | differentiated |

*Figure 1.        Research overview on online sentiment and corresponding stock market movements.*

## 2.2    Differential emotions and the financial market

Emotion research has received substantial attention by previous research and, consequently, produced a comprehensive set of findings regarding the impact of emotions on the financial market (Ackert et al., 2003). In general, these findings support the assumption that emotions distributed through social

interaction affect the traders' decision-making process which in turn affects the stock market prices, trading volume, market volatility, and can even cause stock market bubbles (Nofsinger, 2005).

When studying emotions, researchers generally distinguish between emotions as distinct-states or dimensions. While state-theorists examine each emotion as unique and distinct from all others (e.g., Ekman et al., 1969; Izard, 1993) proponents of the dimensional approach identify elemental dimensions along which they position emotions and which account for similarities and differences among affective states (e.g., Larsen and Diener, 1992; Russell, 1980; Watson and Tellegen, 1985). In a critical reconsideration of these different approaches Ekkekakis (2013) integrated both understandings into one model of the hierarchical structure of the affective domain. Based on the models of Nesse (2004) and Shaver et al. (1987), he developed a framework which understands the affective domain to be hierarchically organized with basal dimensions (i.e., valence and activation) as an evolutionary basis for seven more differentiated emotional states (i.e., love, joy, pride, fear, anger, sadness, and shame). When applying automated sentiment analysis, IS researchers have predominantly focused on measuring the bipolar valence dimension of positive-negative emotionality (e.g., Sprenger et al., 2014b). However, the undifferentiated dimensional approach implies a lower degree of specificity which can only be overcome through the assessment of distinct emotional states (Ekkekakis, 2013). Thus, in this study we include the more refined emotional states in addition to the basic valence dimension. We also consider the activation dimension by measuring the strength of each emotion.

The *valence* dimension describes the evaluative character of an emotion which determines whether something is perceived as pleasant (also termed positive) or unpleasant (also termed negative) (Elster, 1998). While IS research has been almost exclusively focused on the analysis of the average emotionality (Li et al., 2014), recent findings demonstrate the importance of distinguishing between positive and negative valence when investigating the impact of microblogging sentiment on company-specific stock market reactions (Smailović et al., 2013; Sprenger et al., 2014a). From an evolutionary perspective, negative emotions have been found to be more decisive for survival and, thus, became prevalent in modern society (Nesse, 2004). Also, on social media platforms negative messages spread more easily than positive news (Kimmel, 2010) and receive more attention (Luo, 2007). Furthermore, studies analysing the differential effects of positive and negative emotions on stock prices have found a stronger relation between unpleasant news (Chan, 2003), negative trader mood (Dowling and Lucey, 2008), and the occurrence of unfavourable events (Edmans et al., 2007) compared with the positive equivalents. Consequently, company-specific negative user-generated content is more thoroughly processed and has more explanatory power of abnormal returns than positive information (Li et al., 2014; Oh and Sheng, 2011; Tirunillai and Tellis, 2012). However, it needs to be acknowledged that the price reaction to negative tweets seems limited to the day itself, which corresponds to the investigated time effects in this study (Sprenger et al., 2014a). Therefore, we assume that negative messages as opposed to positive ones receive more attention, are considered more seriously, and affect the decision-making process more deeply. Thus, we propose the following:

*$H_{1a}$: The strength of the positive valence of the message sentiment about a company is unrelated to the company stock prices.*

*$H_{1b}$: The stronger the negative valence of the message sentiment about a company, the lower the company stock prices.*

The following elaboration of the differential emotions refers to general descriptions and established characteristics from prior literature with the purpose of providing working definitions of the emotions considered in this study. We outline mutual distinctions broadly derived from Ekkekakis (2013) and his predecessors (Nesse, 2004; Shaver et al., 1987) rather than comprehensively define emotions.

*Positive emotions* are generally advantageous in situations that offer opportunities or when goal attainment progress is faster than expected (Nesse, 2004). We analyse three different positive emotions in this study: Affection, Happiness, and Satisfaction. The emotion of love encompasses the generic form of companionate love which applies to friendship, family relationships, marital relationships, etc. and passionate love which refers only to romantic or sexualized love. Both forms share a core concept

of *affection* that includes fondness and liking which is considered more appropriate in this context. It promotes a personalized feeling of well-being that is attributed to a particular person or object and causes an overemphasis of the positive side of things (Shaver et al., 1987). *Happiness* is a generic sub-category of the more general emotion joy and resembles the conceptual counterpart of depression (see below). It is triggered in situations where a positive outcome in the achievement (e.g., task success) or social domain (e.g., receiving esteem or affection) has been realized by attaining something desired or desirable. The happy person adopts a positive outlook on future events, becomes socially outgoing, and communicates the good feelings. While both happy and affectionate people exaggerate prospects, the latter is more energetic and enthusiastic (Shaver et al., 1987). The understanding of the emotion *satisfaction* draws heavily on work from positive psychology as it describes the acknowledgement and contentment when reaching a goal. This goal may be long striven for, predictable, or just predetermined as the level at which it provides satisfaction (Seligman, 2002). Research has found social status (i.e., pride) to be elementary for satisfaction and as such constitutes the conceptual opposite of shame (see below) (Nesse, 2004). While satisfaction is somewhat related to happiness its experience is less energetic and overwhelming (Shaver et al., 1987).

Only a small share of research has investigated the specific effects of positive emotions on stock prices. This research has found significant correlations between factors like sunshine (Hirshleifer and Shumway, 2003; Saunders, 1993), holidays (e.g. Ramadan) (Białkowski et al., 2012), and pre-holiday periods (Teng and Liu, 2013) with stock market data. It is commonly argued that these events promote positive feelings or make people more optimistic which translates into higher stock returns (Ackert et al. 2003). Other studies, however, which analyse comparable effects under additional consideration of negative emotions show that stock market returns are significantly lower during summer and fall than during winter and spring months (Jacobsen and Marquering, 2008). Tetlock (2007) shows that media pessimism is correlated with downward pressure on stock prices and trading volume while no effect was found for positive emotions. This is also in line with the assumptions of prospect theory that emotions affect decision-making especially under conditions of risk and uncertainty (Damasio, 2008; Kahneman and Tversky, 1979). Following the aforementioned explanations, we hypothesize:

*$H_{2a}$: The strength of affection of the message sentiment about a company is unrelated to the company stock prices.*

*$H_{2b}$: The strength of happiness of the message sentiment about a company is unrelated to the company stock prices.*

*$H_{2c}$: The strength of satisfaction of the message sentiment about a company is unrelated to the company stock prices.*

*Negative emotions* arise in situations that pose threats, when the possibility of loss is heightened or a loss has actually occurred (Nesse, 2004). We analyse four different negative emotions in this study: Fear, Anger, Depression, and Contempt. Since especially negative emotions seem to affect financial markets and these have been found to exert unique effects for example on risk taking, in the following we consider each negative emotion separately (Rick and Loewenstein, 2008).

*Fear* is the interpretation of events as potentially dangerous or threatening to the self (physical harm, loss, rejection or failure) which is formed in unfamiliar and unpredictable situations. It encompasses the subcategories horror, in the case of a specifically targeted fear, and anxiety as the generalized correspondence. Both forms share the key experience of uncertainty where the protagonist feels vulnerable and helpless regarding potentially negative events. Fearful persons become aroused, experience inner turmoil and, thus, have limited coping abilities (Shaver et al., 1987). Gilbert and Karahalios (2010) developed an US national anxiety index from LiveJournal websites for which they found a negative correlation with the S&P 500. Moreover, recent studies on Twitter found the consideration of the words "fear", "worry" and the antonym "hope" to increase prediction accuracy of the fall of major market indicators (Porshnev et al., 2013; Zhang et al., 2011). Thus, we assume:

*$H_{3a}$: The stronger the fear of the message sentiment about a company, the lower the company stock prices.*

*Anger* results from interferences of the execution of plans or attainment of goals (e.g., by reducing the individual's power, violating expectations, frustrating or interrupting goal-directed activities). Most commonly, these interferences are perceived as illegitimate and opposite to what ought to be. All different forms of anger (e.g., irritation, exasperation, and torment) share the core feeling of hate. Unlike the fearful flight from the source of danger, anger energizes people to attack or rail against the cause of anger with the purpose of rectifying the perceived injustice. Simultaneously, thoughts are one-sidedly channelled towards the belief of oneself being right and the other being wrong (Shaver et al., 1987). Research generally found a down pressing effect of an agitated word of mouth and an upset social mood on the company stock returns (Luo, 2007; Nofsinger, 2005). We therefore predict:

*H3b: The stronger the anger of the message sentiment about a company, the lower the company stock prices.*

*Depression* constitutes the prototypical form of sadness where a person feels powerless, helpless, or impotent to change an aversive situation and cognitions ruminate about these unhappy circumstances (e.g., suffering, disappointment, neglect). In contrast to fear, depression is not anticipatory but caused by a situation in which the threat has already been realized. Thus, a depressed person has experienced an undesirable outcome that the fearful person dreads (e.g., death of a significant other or social rejection). Since depression refers to a (negative) occurred event, it constitutes the opposite concept of happiness. Considering that the aversive event has already happened, attempts to flee (like fear) or becoming energized in order to fight (like anger) are useless. Therefore, the sad person decreases activity, shows withdrawal, gives up, and withholds efforts to improve circumstances (Shaver et al., 1987). A substantial body of research has shown the connection between depressive environmental effects like the seasonal affective disorder (e.g., Dowling and Lucey, 2008; Kamstra et al., 2003), cloudier days (Chang et al., 2008), and disasters (Kamstra et al., 2000) with decreasing returns. In their seminal work on Twitter messages and financial data, Bollen et al. (2011) found a predictive value of the conceptionally related calmness factor on stock prices. Thus, we hypothesize:

*H3c: The stronger the depression of the message sentiment about a company, the lower the company stock prices.*

*Contempt* is the emotional response of revulsion to something considered offensive or unpleasant. In our understanding, it forms the core emotion of shame and represents the social correspondence of biological disgust *(Tybur et al., 2009)*. It is as an evaluative reaction towards occurrences of negative social value (e.g., lying, theft, murder, and rape) which motivates the desire for social distance as well as avoidance of offensive things (Sherman and Haidt, 2011). The emotion of contempt is assumed to control moral behaviour by signalling that certain behaviours or entities are to be avoided in order to preserve group cohesion (David and Olatunji, 2011; Tybur et al., 2009). Considering its strong connection with social status, contempt is theorized as the conceptual opposite of satisfaction (Nesse, 2004). Research regarding the financial effects of contempt in the social mood towards companies is scarce. Regarding the individual trader, Harrington (2012) finds individual forms of coping with contempt (i.e., avoidance, denial, reframing, and guilt) which inspire different behaviours and volatile outcomes. Since, we do not find empirical evidence for the distinct impact of contempt, we assume:

*H3d: The strength of contempt of the message sentiment about a company is unrelated to the company stock prices.*

In the following, we describe the empirical analysis conducted to test our hypotheses.

# 3 Empirical Study

## 3.1 Case description and data collection

In the first step, we *selected the sample* of companies whose stock prices we wanted to analyse. Initially, we started with a list of 100 companies from varying industry sectors that constitute the S&P 100

Index. In line with related research we considered the S&P 100 Index which constitutes a representative cross section of the overall US equities spectrum, encompassing various industries with well-known companies which are of considerable public interest and thereby trigger sufficient social media messages (e.g., Sprenger et al., 2014b). Next, we removed all companies from the sample that have ambiguous names (e.g., Apple, Google, and UPS) to reduce data noise. To address data volume restrictions we conducted a two-stage random sampling method of the remaining companies. In the first stage we separated them into three groups of 20 companies based on the standard deviation of the companies' market value within the S&P 100 Index: large, medium, and small companies. In the second stage we randomly selected eleven companies from each of these three groups for further analysis.

During the second step of *data collection* we used a certified social media provider to access social media data and Yahoo!Finance to obtain the NYSE daily closing values. Regarding the social media data, we collected messages in English language from the microblogging platform. We identified 111 keywords comprising various spelling versions of company names to collect tweets from and about the selected companies. Each tweet that contained exactly one of the keywords was considered for further analysis to ensure unambiguity of our automated analysis (Sul et al., 2014).The data access from the professional social media data provider enabled us to collect 100 percent of the messages that explicitly mention the company name (keyword sample). Thereby, we avoid common biases from the download rate restrictions of the public API access like the underrepresentation of retweets, temporary interruptions, or data fidelity. The keyword sample also prevents distortions from the less resource intensive tracking of hashtagged tweets (Bruns and Stieglitz, 2013). As result, we collected 6,567,239 tweets that address one of the selected 33 companies during the period of January to March 2014.

The third step comprised the *cleaning and pre-processing* of the Twitter data for the subsequent analysis to address increased noise issues of less topic specific non-cashtag messages (Sprenger et al., 2014b). Initially, we manually screened the user tweets for usernames which were erroneously collected because they included one of the keywords but did not contain information about the companies themselves (e.g., CITI_MEDIA). Hence, tweets contributed by 1,261 users as well as tweets directed towards them were removed from the data sample. Additionally, we screened the data for messages not related to the company (e.g., containing the name of a company sponsored sports arena) and consequently excluded tweets based on the 1,146 accordingly identified terms. In the last cleaning step, to exclude spamming users we considered the individual share of followers and tweets as an exclusion criterion. Based on a rule of thumb we deleted all tweets sent from users with zero followers and more than 50 messages as well as messages from users with fewer than 100 followers and a tweets-to-followers-ratio of 1000 or higher. In essence, we deleted 15% noisy tweets which results in the final dataset of over 5.5 million tweets.

## 3.2    Method and Measures

### 3.2.1    Directed content analysis procedure

We conducted a manual directed content analysis to develop the emotions categories for the differential sentiment analysis of Twitter messages. A directed content analysis enables to classify text into specific categories based on an explicit coding scheme which is deduced from established theory and prior research findings to ensure systematic, replicable, and valid inferences (Hsieh and Shannon, 2005; Krippendorff, 2012). In this study, we classified an existing set of emotion words into established emotion states. For this purpose, on the one hand, we used the emotion words from the lexicon of the established sentiment tool "SentiStrength 2" (Thelwall et al., 2012). On the other hand, we considered the descriptions from the emotion model of Ekkekakis (2013) to define the emotion states.

It was decided to use the SentiStrength lexicon developed by Thelwall et al. (2012), because it is specialized in analysing the sentiment of short informal texts and provides a comprehensive list of emotion words. Accordingly, it has proven to be the most elaborate approach for the analysis of mi-

croblogs compared with other popular word lists (e.g. ANEW or AFIN) (Nielsen, 2011). Moreover, by providing validated scores for the strength of each emotion word SentiStrength allows us to also account for the valence dimension of each emotion (Ekkekakis, 2013). The applied lexicon is derived from the General Inquirer dictionary adjusted with human polarity coding and strength judgments comprising more than 2,300 emotion words (Thelwall et al., 2012).

Initially we inferred the key emotional coding categories (i.e., Affection, Happiness, Satisfaction, Fear, Anger, Depression, Contempt) and afterwards built category specific operational definitions based on theory and literature (Potter and Levine-Donnerstein, 1999). To avoid potentially impairing effects of subjectivity (Harwood and Garry, 2003) we objectified the content analysis by abiding established principles along the entire process. Thus, we followed Morris' established 5-step process for manual content analysis as will be described in further detail hereafter (Morris, 1994).

The first step was to determine the unit of analysis for the coding process. Since sentiment analyses commonly apply dictionary-based algorithms that screen documents for distinct predefined emotion words, we adopted the single emotion words from the SentiStrength lexicon as the unit of analysis.

Secondly, we referred to established theories (Morris, 1994; Rourke et al., 2001) to develop the coding scheme for the respective emotion states based on the work of Ekkekakis (2013) and his precursors (Nesse, 2004; Shaver et al., 1987). Furthermore, we discussed the adaptation of the coding scheme to the microblogging context among a panel of three researchers who were familiar with the theoretical background. Subsequently, the coding scheme was repeatedly revised during the following process until the final version (see below) was established. For the valence dimension we maintained the validated and predefined classification of positive and negative words.

In the third step, we conducted a first training section with three independent coders to build up their familiarity with the scheme and establish objectivity of the judges (Kolbe and Burnett, 1991). It is the task of a coder to allocate an emotion word to a particular emotion category based on the descriptions from the coding scheme. The training comprised the independent test-coding of a representative sample of 100 training messages by two assistant and one affiliated researchers (Lombard et al., 2002). Afterwards, the results were compared, discussed, and the coding schemata revised accordingly.

During step four we iteratively conducted a second coder training of the three researchers with alternative datasets to establish the reliability of the coding scheme. In accordance with accepted guidelines, we used a data sample of 100 messages and calculated the reliability scores for each iteration until reaching an acceptable level (Harwood and Garry, 2003). Following each iteration, apparent discrepancies were discussed among the coders and the coding scheme was revised accordingly (Morris, 1994; Sprenger et al., 2014b). For example, in the second revision round we added the category "none of them" for words that would fit neither of our defined emotion states (e.g., injury). The reduction in lexicon words was in concordance with the assumption of Ekkekakis (2013) that the analysis of singular emotion states does not fully correspond to the analysis of the underlying valence dimension. Satisfactory reliability scores – considering the large number of coding categories – in the conservative Krippendorff's alpha and Fleiss' kappa (Lombard et al., 2002; Wever et al., 2006) of above .70 were reached after three iterations (Krippendorff, 2004; Neuendorf, 2002).

Ensuing from this final coding scheme, in the last step one author processed all 2,319 emotion words from the original SentiStrength wordlist to build the differentiated lexicon. While we acknowledge that intercoder reliability is commonly assessed based on the coding results of the entire data sample, it is a popular approach for large datasets to rely on a data share (D'Aveni and MacMillan, 1990; Lombard et al., 2002). The descriptive results of the final differentiated dictionary (see table 2) show a similar predominant share of negative emotion words compared with the original word list. Especially the emotion state "anger" subsumes the largest share of words (approx. 47% of all negative words) while "affection" has the largest amount of positive words (approx. 42% of all positive words).

### 3.2.2 Model based operationalization of differential emotions

Based on the concept of seven different emotion states in the model of hierarchical structure of the affective domain (Ekkekakis, 2013), we considered the emotion expressed by each sentiment word as key concept for the coding categories. The operationalization of emotions was derived from the detailed descriptions in the emotion framework (Ekkekakis, 2013; Nesse, 2004; Shaver et al., 1987). The coder was advised to adopt a first person perspective. Following the model's assumption that each emotion is a distinct-state, each word was exclusively categorized into one category (table 1).

| Emotion | | Description | Emotion Word | Example from data sample |
| Valence | State | | | |
|---|---|---|---|---|
| Positive | Affection | Genuine fondness and liking that is attributed to a particular person or object. | Love, Longing, Adoration | *I'm loving the new @DukeEnergy logo. Well done! http://t.co/CreLUK9WdY* |
| | Happiness | Amplified enthusiasm and excitement about attaining something desired or desirable. | Joy, Terrific, Amusement | *I think it's awesome that @CVS_Extra is removing tobacco products from their stores. Makes me happy that they are my pharmacy!* |
| | Satisfaction | Proud acknowledgement of and contentment with reaching a predetermined goal. | Pride, Success, Contentment | *RT @AccentureCAS Over 80 delegates from 20 leading CG companies attended the hugely successful Accenture CAS User Forum in Atlanta.* |
| Negative | Fear | Anticipatory horror or anxiety in unpredictable or potentially harmful situations. | Terror, Horror, Anxiety | *@officialknewton @newtonrw have you ever put a penny in some coca cola? Frightening what it could be doing to our insides.* |
| | Anger | Animated animosity towards malice that can motivate rectification. | Hate, Outrage, Irritation | *I hate Texas Instruments and all of their evil creations.* |
| | Depression | Impeding sadness evoked by an aversive event that may hinder activity. | Sadness, Hopeless, Disappointed | *Sad day for all of the @UnionPacific family. Sad to see such a good man and CEO be taken by a vicious disease but he's in a better place* |
| | Contempt | Revulsion to something considered socially offensive or unpleasant. | Guilt, Shame, Disgust | *Don't work for Bank of America ever. They have no loyalty to their employees. Absolutely despicable.* |

*Table 1.        Overview of the seven different emotions and their operationalization.*

A word was classified as affection when it described admiration (e.g., *worship, graceful*) or personal appreciation (e.g., *handsome, liking, pretty, wonderful*). Also more passionate appraisals (e.g., *beloved, warmheart, cutie*), trustful expressions of consideration (e.g., *care, compassion, support*), and positive estimates of relationships (e.g., *homie, friend, mate*) were co ded into this category. Happiness was considered whenever someone expressed joyful excitement (e.g., *overjoyed, terrific, thrilling*), a high level of activity (e.g., *lively, dynamism, ecstatic*) or a positive attitude (e.g., *optimistic, carefree, easygoing*). Similarly to affection, words of appreciation were included (e.g., *delightful, fabulous, wicked*) while for happiness these were less personalized and prolonged. Satisfaction, on the contrary, applied to achievement oriented emotion words that described reaching a goal (e.g., *accomplish, triumph, success*) and the associated intrinsic (e.g., *confident, content, pride*) as well as extrinsic consequences (e.g., *compliment, glory, reward*).

Regarding the negative emotions, fear was coded when a sentiment addressed an unpleasant apprehension (e.g., *anxious, concern, distraught*) of a potentially harmful event (e.g., *complication, chaos, catastrophe*). Also words that revolved around possible consequences (e.g., *doom, threat, danger*) or rudimentary coping mechanisms (e.g., *avoid, doubt, fright*) of these dreaded occasions were included. The emotion anger applied to words that express aversion ranging from animated antagonism (e.g., *furious, detest, antagonize*) up to agonized rail (e.g., *bloody, crappy, shoddy*) or personal insults (e.g., *bastard, fool, jerk*). Moreover, the category included descriptions of the disclined attitude towards the aggravating object (e.g., *animosity, grudge, hate*). Depression comprised the communication of the experience of a saddened condition (e.g., *cheerless, bitter, crushing*) and of its evoking event (e.g., *burden, calamity, misfortune*). Words that express diminished coping capabilities (e.g., *apathy, breakdown, resignation*) and dismal prospects (e.g., *aimless, discourage, futility*) were also included in this coding category. Ultimately, contempt was classified for socially offensive actions (e.g., *adultery, bribe, affectation*), the personal evaluation of the respective behaviour (e.g., *amoral, deceitful, despicable*), and the sentiment following the contemptible event (e.g., *awkward, guilt, shame*). Expressions that signal consequent punitive behaviours were also incorporated (e.g., *condemn, detract, evade*).

### 3.2.3    Differentiated sentiment analysis

Subsequently, we assessed the differentiated emotions of every tweet with an automated unsupervised sentiment analysis (see table 2). Therefore, we deployed the SentiStrength tool (Thelwall et al., 2012) with the previously developed emotion specific lexicon. The underlying algorithm is specialised in the analysis of microblogs because it accounts for a variety of grammatically wrong but in social media often used forms of writing. Furthermore, it applies wild cards (e.g., terrific*), or the so-called Kleene star stemming to increase the successful classification of different word variations.

The sentiment analysis follows a dictionary-based approach comprising two consecutive steps: determining the presence of an emotion and classification of the emotion strength (Liu, 2010; Wilson et al., 2005). For the purpose of the study, we applied the differentiated dictionary to assess the valence and the different emotion states expressed in the messages. Apart from the sentiment lexicon, some other lists of words or word groups were considered as well. Expression like "very" and "may" serve as booster words which lead to an increase or decrease in strength of a following emotion word. Ultimately, the SentiStrength algorithm computes a sentiment score between 1 and 5 separately for each emotion in a given message based on the particular sentiment strength expressing the activation of an emotion. Thereby, we account for potential co-occurrences of multiple emotions within a single message by simultaneously identifying the strength separately for each emotion state. The overall valence of a message was determined by the respectively highest sentiment score.

Afterwards, we transformed the data into day specific measures separately for each company. First, we computed the average positivity ($Pos_{Avg}$) and negativity ($Neg_{Avg}$) based on the sum of the particular valence strength relative to the respective number of messages including neutral ones (*Hypothesis $1_a$ and $1_b$*). We included the number of neutral messages to avoid problems of collinearity and account for the unemotional Twitter content. The emotion state specific average measures were calculated comparably. For the positive emotions predictors ($Affection_{Avg}$, Happiness$_{Avg}$, and Satisfaction$_{Avg}$), we used the sum of the specific emotion strength relative to the number of positive messages including neutral ones (*Hypotheses $2_a$-$2_c$*). The negative emotions predictors ($Fear_{Avg}$, Anger$_{Avg}$, Depression$_{Avg}$, and Contempt$_{Avg}$) were calculated respectively with the number of negative and neutral tweets in the denominator (*Hypotheses $3_a$-$3_d$*). Finally, it needs to be noted that we aligned the time of the tweet with the stock data. Since the goal of this study is to investigate the explanatory power of differentiated emotions, we used the lagged tweets between two NYSE trade closings to analyse the stock closing values. This means, for example, that all tweets sent after 4:00 p.m. Eastern Time were associated with stock prices of the following day because these messages can only affect the market indicators of that next day (Sprenger et al. 2013). The remaining steps of data analysis are described in the following.

| Descriptive Statistics | | Positive | | | Negative | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Affection** | **Happiness** | **Satisfaction** | **Fear** | **Anger** | **Depression** | **Contempt** |
| **Dictionary** | Absolute [#] | 163 | 123 | 87 | 245 | 676 | 312 | 432 |
| | Rel. Freq. [%] | 7.998 | 6.035 | 4.269 | 12.022 | 33.17 | 15.309 | 21.197 |
| **Sentiment Analysis** | Absolute [#] | 21,161 (39,343) | 19,302 (35,856) | 21,661 (30,205) | 7,453 (9,392) | 20,372 (28,748) | 8,682 (10,336) | 8,684 (10,761) |
| | Rel. Freq. [%] | 12.58 (5.11) | 11.47 (4.3) | 12.88 (3.66) | 4.43 (2.72) | 12.11 (4.72) | 5.16 (2.77) | 5.16 (3.18) |

**Dictionary.** Descriptive statistics for the classification of emotion words in the differentiated dictionary.
**Sentiment Analysis.** Descriptive statistics for the number of messages per company classified in the differentiated sentiment analysis.
**Statistics.** Absolute = Total number; Rel. Freq. = Relative frequency; standard deviations in parentheses below mean.

*Table 2.        Descriptive statistics for the dictionary and the respective sentiment analysis.*

## 3.3     Empirical analysis and results

We conducted two fixed effects panel regression with robust standard errors to test our hypotheses. This approach enabled us to control for (1) any invariant a-priori idiosyncratic differences among the companies through the restricted fixed effects assumption, (2) for common control variables such as the pre-holiday effect (*pre_holiday*), daily return of the S&P 500 Index (*return_SP500*) or company earnings releases during our data collection (*earnings*), and (3) the day and month specific effects (which are not displayed in the tables for the sake of clarity) additionally to the consideration of the focal effects of separated emotional valence (*Model 1*) and differentiated emotion states (*Model 2*) (Wooldridge, 2012). A comprehensive analysis of collinearity revealed tolerance values greater than .1 and VIF values below 10 (mean = 1.46), and thus showed no sign of multicollinearity (Belsley, 1991).

| Predictor Variables | Model $_1$ | | | | | Model $_2$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | SE | T | VIF | Tol. | Coeff. | SE | T | VIF | Tol. |
| constant | .002* | (.0001) | 2.45 | --- | | .003** | (.001) | 2.27 | --- | |
| earnings | -.005 | (.005) | -0.93 | 1.04 | .958 | -.006 | (.005) | -1.15 | 1.13 | .881 |
| return_SP500 | .998*** | (.059) | 16.84 | 1.25 | .798 | .997*** | (.6) | 16.7 | 1.26 | .797 |
| pre_holiday | .002 | (.001) | 1.44 | 1.17 | .858 | .002 | (.001) | 1.62 | 1.17 | .856 |
| *Pos$_{Avg}$* | .0001 | (.002) | -0.12 | 1.34 | .748 | --- | | | | |
| *Neg$_{Avg}$* | -.003** | (.002) | 2.11 | 1.32 | .759 | --- | | | | |
| *Affection$_{Avg}$* | --- | | | | | .0003 | (.003) | 0.1 | 1.36 | .738 |
| *Happiness$_{Avg}$* | --- | | | | | -.007* | (.004) | -1.83 | 1.34 | .744 |
| *Satisfaction$_{Avg}$* | --- | | | | | .004 | (.003) | 1.29 | 1.25 | .801 |
| *Fear$_{Avg}$* | --- | | | | | .0006 | (.002) | 0.29 | 1.14 | .88 |
| *Anger$_{Avg}$* | --- | | | | | .001 | (.002) | 0.66 | 1.2 | .836 |
| *Depression$_{Avg}$* | --- | | | | | .009*** | (.003) | 2.89 | 1.14 | .89 |
| *Contempt$_{Avg}$* | --- | | | | | .003 | (.004) | 0.79 | 1.17 | .857 |
| Model Statistics | $F_{11,32}$ = 56.46, p <.001***, $R^2_{within}$ = 0.36 | | | | | $F_{16,32}$= 58.24, p <.001***, $R^2_{within}$ = 0.3626 | | | | |

**Statistics:** Coeff. = Regression Coefficient; SE = Standard error; VIF=Variance Inflation Factor; Tol.= Tolerance; $R^2_{within}$ = percentage of variance in stock price changes explained through changes within predictors
**p-values:** *** p < 0.001 highly significant; ** p < 0.05 significant; * p < 0.1 tendential significance

*Table 3.        Results of the fixed effects panel regression of the different emotions on stock prices.*

The results of the panel regression (see table 3) generally support our underlying assumption that the differentiated sentiment has explanatory power for the company-specific stock price developments. For example, *Model 1* shows that the stronger the negative sentiment towards a company the lower its stock price (T=2.11, p < .05; *Hypothesis 1$_b$*), while the strength of the positive sentiment was unrelated to stock price movements (T=-0.12, p > .1; *Hypothesis 1$_a$*). On a side note, a corresponding fixed effects panel regression with the average sentiment – as opposed to this valence separated one – showed no explanatory power for the stock market (*All$_{Avg}$* = 0.002 (0.001), T = 1.55, p >.1$_{n.s.}$). The subsequent analysis of the distinct emotions (*Model 2*) shows more precisely which emotions correspond to financial market developments. In line with our hypotheses, we did not find a significant effect of affection (T=0.1, p > .1; *Hypothesis 2$_a$*), satisfaction (T=1.29, p > .1; *Hypothesis 2$_c$*), and contempt (T=0.79, p > .1; *Hypothesis 3$_d$*) on stock price movements. Opposed to findings on general market indices, in this context of company-specific stocks we could not find a significant effect of fear (T=0.29, p > .1; *Hypothesis 3$_a$*) and anger (T=0.66, p > .1; *Hypothesis 3$_b$*) on stock movements. However, the results revealed that the emotion driving effect of negative emotionality is depression, which is the only negative emotion with a significantly negative regression coefficient (T=2.89, p < .01; *Hypothesis 3$_c$*) under simultaneous consideration of all emotion states. Considering the theoretical foundation of these measures, it seems that while general stock market indices are influenced by the anticipation of hypothetical aversive events (i.e., fear), company stocks are only influenced by events that have actually occurred. This would also explain why happiness – which constitutes the conceptual opposite of depression – also affects stock prices significantly (T=-1.83, p < .1; *Hypothesis 2$_b$*). The surprisingly negative effect of happiness could be explained by the distinction between immediate and expected emotions by Rick and Loewenstein (2008) who elaborate that positive emotions might make investors more risk-avoidant by trying to avoid a disturbance of positive feelings. In a similar vein, Zhang et al. (2011) found evidence that the amount of expressed emotions and not the specific type (i.e., fear, worry, and hope) causes a market index decrease. However, more research is needed to ultimately resolve this issue. Generally, considering that happiness has a significant effect while the average positivity is not associated with stock prices shows again the importance of investigating single emotions separately. Table 4 presents an overview of the investigated hypotheses and findings.

| Hypothesis | Finding |
|---|---|
| H$_{1a}$: The strength of the positive valence of the message sentiment about a company is unrelated to the company stock prices. | Supported |
| H$_{1b}$: The stronger the negative valence of the message sentiment about a company, the lower the company stock prices. | Supported |
| H$_{2a}$: The strength of affection of the message sentiment about a company is unrelated to the company stock prices. | Supported |
| H$_{2b}$: The strength of happiness of the message sentiment about a company is unrelated to the company stock prices. | Not Supported |
| H$_{2c}$: The strength of satisfaction of the message sentiment about a company is unrelated to the company stock prices. | Supported |
| H$_{3a}$: The stronger the fear of the message sentiment about a company, the lower the company stock prices. | Not Supported |
| H$_{3b}$: The stronger the anger of the message sentiment about a company, the lower the company stock prices. | Not Supported |
| H$_{3c}$: The stronger the depression of the message sentiment about a company, the lower the company stock prices. | Supported |
| H$_{3d}$: The strength of contempt of the message sentiment about a company is unrelated to the company stock prices. | Supported |

*Table 4.        Overview of the empirical findings regarding the research hypotheses.*

# 4      Discussion and Conclusion

The goal of this study was to analyse the explanatory power of differentiated emotions expressed in tweets for company-specific stock prices. Specifically, we focused separately on emotions with positive (affection, happiness, and satisfaction) and negative valence (fear, anger, depression, contempt). Based on established emotion research (Ekkekakis, 2013) and sentiment analysis (Thelwall et al., 2012), we developed and applied an open source emotion-specific dictionary that also considers the underlying valence and activity dimensions. By analysing daily closing values of 33 S&P 100 companies over the period of three months, this study provides three key findings: (1) the differentiated emotions are more strongly associated with company-specific stock price changes than the undifferentiated average sentiment, (2) negative emotions generally have a higher explanatory power, and (3) especially the strength of emotions referring to specific events (depression and happiness) account for price movements. Based on the results of our analysis we will discuss implications of our findings for theory and practice and point out the potential for future research as well as limitations.

## 4.1     Implications for Theory and Practice

This study offers substantial contributions to research and practitioners alike. To the best of our knowledge, we are the first to advance research to the field of company-specific stock price analysis based on differentiated emotions. Thereby, we overcome existent limitations of the few other differentiated sentiment analyses which have not considered the activity or strength of an emotion (Porshnev et al., 2013), do not respect the exclusiveness of emotion states (Baccianella et al., 2010), or withhold detailed insights into the classification of emotions (Bollen et al., 2011). On the contrary, we provide access to the dictionary for practitioners to apply and researchers to also refine and advance the differentiated sentiment analysis to other important fields of application like event studies (Sprenger et al., 2014a). In this regard, we address calls from research by supporting the comprehensive analysis of events that affect company values, the companies' pattern of responses and market reactions (Tetlock, 2007) and advancing the efforts of developing methods to understand information percolation with its effect on stock markets (Li et al., 2014). The evidence presented for the necessity of a more differentiated sentiment analysis is equally relevant for practice considering that currently the New York Stock Exchange (NYSE, 2014) and High Frequency Trading (Groß-Klußmann and Hautsch, 2011) limit the social media analysis to the binary emotional valence. Thus, practitioners should include an emotionally more differentiated sentiment analysis in their trading algorithms.

## 4.2     Limitations and Future Research

The implications of this study must be considered in the light of their limitations that also provide a basis for future research. The results are limited in their generalizability to microblogging platforms and to the western culture since we only considered tweets in English and NYSE stock prices. However, the expression and impact of emotions has been found to vary across cultures (Matsumoto and Ekman, 2004). Moreover, it could be assumed that the common larger dictionary for negative than for positive emotions also present on our dictionary might cause bias towards the bigger influence of negative emotionality (e.g., Nielsen, 2011). Future research will need to compare the impact of single actually identified words and the number of words within sets of message.

Furthermore, Sprenger et al. (2014a) found time-related effects for positive and negative emotions. Future research should analyse potential intraday and day outlasting effects of differential emotions. Also, the interplay of different emotions needs to be considered as, for example, depression has been found to have a competing effect to anger on risk- taking (Cao and Wei, 2005). Lastly, we intend to analyse whether different emotions are more important in other environments such as customer care, where anger might be expressed more openly.

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