Emotions and their Impact on Investor Behaviour

A thesis

submitted in fulfilment

of the requirements for the degree

of

Doctor of Philosophy in Finance

at

The University of Waikato

by

Ahmed Khan

KO TE TANGATA

THE UNIVERSITY OF

WAIKATO

Te Whare Wānanga o Waikato

2022

Abstract

Decision-making is often considered to be a rational and cognitive process; however, recent literature shows that human emotions play a very important role in the decision-making process. Despite the overwhelming evidence from the psychology literature, there has been little recognition and consideration for the role of human emotions in financial decision-making. In order to cover this research gap, our study examines the relationship between emotions proxied by the news and social media and the decision-making process of investors. The 10 different emotions that we evaluate are calculated on an ongoing basis by applying advanced algorithms which scan listings on the news and social news media. Our sample consists of firms listed on the S&P500 and covers the 20 years from 1998 to 2017. We recognise that there are two channels through which emotions impact on market valuations: one being a direct impact and the other being an indirect path through which emotions condition how investors respond to information signals.

The first empirical chapter of the study investigates the impact of emotions on investor behaviour at the time of the earnings announcement. We find that Aggregate_Emotion, the aggregate across our individual emotions, has a significant impact on the decision-making of investors, as does the aggregate of both the positive and negative emotions considered. Our findings concerning individual emotions are mixed: while optimism and joy, and stress and gloom all impact on investor decision, anger and fear prove to be emotions that have little or no impact on investor behaviour. We also consider the relative impact of the two media sources, and we reveal mixed findings. For example, with social media, we find the greatest influence with respect to love/hate, whereas, for the news media we see a greater influence in the case of trust.

The second chapter studies the impact of emotions during the post-earnings announcement drift (PEAD). PEAD is one of the longest surviving anomalies that challenge the efficient market hypothesis. While several studies have identified factors such as liquidity risk, arbitrage risk, and unsophisticated investors etc. that cause PEAD to persist, our results show that human emotions are yet another factor that plays a role in explaining the existence of this long-standing anomaly. Our results suggest that the drift can be explained by both the level of emotions at the time of the announcement but even more so by the direction of the level of emotions during the post-announcement period. All the individual positive emotions contribute towards how the investors value stocks over the post-announcement period, whereas the results for individual negative emotions are a bit weaker when compared to positive emotions.

Finally, in the third empirical chapter, the focus is on identifying whether it is possible to use available information on human emotions to identify and exploit mispricing in stock pricing. Using the insights from the first two empirical chapters, we develop a two-part strategy that invests in the firms on the basis of aggregate positive and negative emotions. The first part of the strategy involves going long(short) when there is an exceedingly positive(negative) earnings announcement, and the positive(negative) emotions are in the bottom quartile before the earnings announcement. In the second part, we reverse the trade when the emotion either increases by a pre-specified amount or we reach the end of a pre-specified period. Our investment strategy(ies) produces significant positive returns, even after we take account of trading costs and factor exposures.

Efficient Market Hypothesis (EMH) argues that in a well-functioning financial market, new information gets instantly reflected in the stock prices. Our results are at odds with EMH and show that emotions can cause underreaction at the time of the release of new information.

Furthermore, we also show that there is no automatic correction of the stock prices in the post-announcement period as the direction of the stock valuations is influenced by the direction that emotion takes in the post-announcement period. Overall, the results of our studies show that emotions play a significant role in impacting the decision-making process of investors and shaping stock prices.

Acknowledgements

In the name of Allah, the most beneficent, the most merciful

First and foremost, I would like to express my deep gratitude to my chief supervisor, Professor Ron Bird, who encouraged, motivated, guided, and supported me during my PhD journey. His knowledge and experience in this area is immense. Without his support, completing my thesis would have been impossible. You have been a power of inspiration, Thank you, Ron. I appreciate my co-supervisors, Dr Martin Bai and Dr Peng Huang for their advice and support.

I would also like to thank Professor Frank Scrimgeour for his support throughout my thesis. He was always there to listen to me and provide solutions to my problems. My special thanks also go to Dr Danny Yeung for his advice, support, insightful criticism and encouragement. I also thank him for providing important data for the completion of my thesis.

Thanks also to the staff members and PhD students from the School of Accounting, Finance and Economics for their constructive feedback during seminars.

I would also like to thank Professor Dr Zafar Iqbal Jadoon who encouraged me to start my PhD journey. I learned a lot from him and would like to dedicate this thesis to him.

Firstly, I would like to thank my wife who shared every moment of this journey with me. Kainat, without your love, support and sacrifices, I would not have reached this point. Thank you for believing in me and for sacrificing most of the time that I should have spent with you but I spent on my PhD journey. I would also like to dedicate this thesis to my two lovely daughters, Parishay Khan and Anushay Khan. Thank you for always reminding me why I started this journey with your cute smiles, hugs, and love.

Finally, my special thanks go to my mother who I love the most in this world. Staying away from her was the toughest thing for me. She encouraged me throughout my educational career. I would also like to thank my superhero father who is a role model for me and supported me throughout my PhD journey. My sincere gratitude to my siblings Dr Saman Yousfi, Fahad Khan, and Saad Khan who were always there to support me. I would also like to thank my mother and father-in-law for their continuous support.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

Abbreviation	Definition
bps	Basis Points
BTM	Book-To-Market
CAR	Cumulative Abnormal Returns
CBOE	Chicago Board Options Exchange
CRSP	Center for Research in Security Prices
DJIA	Dow Jones Industrial Average
EMH	Efficient Market Hypothesis
EPS	Earnings Per Share
Evol	Earnings Volatility
FQ	Fiscal Quarter
FRB	Federal Reserve Bank of San Francisco
I/B/E/S	Institutional Brokers' Estimate System
MSH	Morgan Stanley High-Tech Index
NUE	Negative Unexpected Earnings
PEAD	Post-Earnings Announcement Drift
PUE	Positive Unexpected Earnings
SD	Standard Deviation
SEC	Securities And Exchange Commission
TRMI	Thomson Reuters Marketpsych Indices
UE	Unexpected Earnings
VIX	Implied Volatility Index
WRDS	Wharton Research Data Services

Chapter 1: Introduction

1.1 Introduction

A person can experience a wide array of emotions such as optimism, joy, trust, fear, stress, gloom, anger, shame, guilt, regret, pride, and others. These emotions have been the subject of academic research for decades in psychology (e.g., James, 1894; Kleinginna & Kleinginna, 1981; Roseman, 1984) and while scholars have been unable to agree on an exact definition of emotions, they have been able to identify several of its characteristics. Emotions are usually acute and are relatively short experiences. They are usually triggered by situational events in a person's environment. They are not everlasting as once the stimulus that triggered the emotion disappears; the emotions will also gradually fade. Additionally, the literature states that emotions can be conceptualized as having two dimensions: i) valence (positive or negative emotions), and ii) arousal (high or low).

The characteristics associated with emotions raise the possibility that they can influence decision-making. The question is whether emotions can cause individuals to diverge from the decisions they make when following a cognitive process (devoid of emotions). The idea that decision-making involves a constant tension between cognition and emotions has driven much research in psychology. Loewenstein (2000) argues that emotions respond to probabilities and outcomes in a very different fashion to the cognitive evaluations of factors such as risk. Further emotions are receptive to situations that usually would play a minor role in cognitive evaluations. Moreover, the effect of emotions is likely to be greater for complex decisions such as evaluating the impact of a company announcement on firm value. Damasio (1994) states that emotions play a significant role in the decision-making process. Forgas (1995) shows that decisions that require greater cognitive processing (i.e., complicated) or which are unanticipated are more likely to influenced by emotions. However, it is also important to point out that emotions do not necessarily lead to suboptimal decisions. For example, it is not exceptional for individuals to feel anxious when making a difficult decision. It has been found that this anxiety will drive individuals towards making a safer choice rather than a potentially more lucrative but risky choice (Lerner, Li, Valdesolo, & Kassam, 2015).

Given the importance of emotions in decision-making, we see an increase in interest in understanding the role that emotions play in economic decisions. However, the literature on the impact of emotions on the financial markets is thin, with most studies focusing only on the effect of sentiment on investors' decision-making. While some studies have tried to explain the relationship between market-wide sentiment and financial market reactions using indirect proxies such as daily sunshine and weather, others have tried to extract emotions from the vocal cues of senior executives. However, Da, Engelberg, and Gao (2015) argue that measures such as voice analysis are not frequently available and can be less reliable. Equally, the use of a market-based measure of sentiment has the downside of being the result of factors other than investor emotions (Da et al., 2015).

As most human emotions are the outcomes of social and interpersonal communication, and the news and social media postings have been used as a direct proxy for human emotions (Kijkasiwat, 2021). By applying semantics to social and news media postings, researchers have been able to study the relationship between emotion and stock prices. Das and Chen (2007), extracted investor sentiment from stock message boards from July 2001 to August 2001, found that sentiment has an impact on the Morgan Stanley High-Tech Index MSH. Tirunillai and Tellis (2012) examined user-generated content for four years and found that abnormal returns and trading volumes are significantly related to the volume of chatter in social media. Bollen, Mao, and Zeng (2011) used textual analysis to measure variations in the public mood as a measure of the ability of social media to predict and demonstrate that the six derived mood dimensions have some predictive power on DJIA returns. Karampatsas, Malekpour, and Mason (2018) evaluated the NYSE and NASDAQ from 2011 to 2015 and found that sentiment plays a vital role in the price adjustment process after an earnings announcement. Shu (2010) demonstrates that minor variations in emotions (i.e., moods) can lead to financial market fluctuations. In particular, improved investor mood increases asset prices. Moreover, the influence of emotion is asymmetric, with mood variations having a greater effect on asset prices when investor mood is good compared to when investor mood is low. In contrast to these other findings, Daszyńska-Żygadło, Szpulak, and Szyszka (2014) suggest that emotions have limited influence, finding an insignificant relationship between investor sentiment and stock returns in several markets.

In summary, the literature supports the proposition that emotions proxied by social and news media may influence investment decisions and, therefore, stock valuations. Most of the studies to date have concentrated on a single measure i.e., sentiment which typically is some ill-defined aggregation across several factors emotions are one of these factors. A critical distinction between these studies and this thesis is that we extend the analysis to incorporate 10 different measures of emotions emanating from the news and social media, while other studies mostly focus on sentiment. Further, we examine two (rather than one) channels by which emotions influence stock valuations: a direct channel and an indirect channel where emotions influence how investors react to information signals.

1.2 Research Questions

The recognition that all individuals are susceptible to emotions and that these emotions may influence their decision-making, is significant. We postulate that once aggregated across market participants, emotion-induced decisions can alter asset prices and move financial markets. The focus of this thesis is to find the impact of 10 different emotions proxied by the news and social media on investors' behaviour. Using the data for companies listed on the S&P 500 from 1998 to 2017, this thesis focuses on the following questions:

1. Do the emotions expressed in the social and news media affect the decision-making of investors?
2. Is there a direct relationship between each of the individual emotions, and their aggregate, proxied by the social and news media postings and the market valuation of a company?
3. Do each of the individual emotions, and their aggregate, proxied by the social and news media postings impact on how investors respond to new information (earnings announcements)?
4. Which of the two sources of emotions (social media and news media) has a greater impact on investor decision-making?
5. Do each of the individual emotions, and their aggregate, proxied by the social and news media postings impact on stock prices over the post-earnings announcement period?
6. Is there a way to use available information on human emotions to identify an investment strategy(ies) that significantly outperforms the market?

The financial data of companies is collected from various sources such as CRSP, Compustat, I/B/E/S, etc. The data on emotions is collected from Thomson Reuters MarketPsych Indices (TRMI).

1.3 Significance of the Study

The thesis contributes to the literature in many areas. First, we contribute to the behavioural finance literature by establishing a relationship between investors' emotions and stock returns. Previously, there has been very limited research on how emotions affect short-term stock returns. Griffith, Najand, and Shen (2019) using TRMI data found that a limited subset of these emotion measures has a small impact on prices at a market index level. Vamossy (2021) created his own measure of average emotions in the ten days prior to earning news announcements and found that high emotion before the announcement may lead to a reversal in the post-announcement period. We differ from previous research in several ways. First, we show that emotions can influence prices in the financial markets through two channels; a channel where the state of mind of the investor conditioned by the emotions directly impacts on the valuation they place on the company, and a second channel where the emotions influence investor reaction to new information emanating from the company (in our case, earnings announcements). In contrast to Vamossy (2021), we argue that emotions are fleeting. Thus, any impact on valuation will be associated with how the investors feel at the time of the announcement (rather than an average emotion level in the lead up period). Furthermore, Vamossy (2021) only considers the emotions engendered by social media and not by the traditional news media.

Second, the findings also add to the growing literature on the impact of external forces on investors' reactions to earnings news. Past studies have shown that the magnitude of the investors' response to an earnings surprise can be influenced by external conditions such as market-wide ambiguity and information uncertainty. Our findings show that emotions can influence the investors' reaction to the news on company valuation. In other words, emotions can influence how investors interpret the implications of the information for the valuation of company. We show that prevailing emotions determine the extent to which investors react to news emanating from the company. For example, a positive emotion will increase the extent to which investors will respond to good news and decrease the extent to which they will react to bad news.

Third, this thesis also adds to the scant literature that explains the contribution of the news and social media in shaping a company's share price. This absence is surprising as news and social media play an increasing role in our everyday life, and by inference, our decision-making process. For example, Deloitte (2008) found that peer reviews directly influence the purchasing decision of 82% of the United States' internet consumers. There is also some evidence in the literature to suggest that the news and social media play a role in information dissemination in the financial markets. Peress (2014) highlighted the importance of the news media in disseminating information by showing that trading volume falls by 12% on days of news strikes. Blankespoor, Miller, and White (2014) demonstrated that companies could judiciously increase liquidity in their stocks by employing Twitter to send investors links to press releases and other company-related news to reduce information asymmetry. This thesis further demonstrates that the emotion garnered from mass media can influence market prices by impacting investors' valuation of companies.

Fourth, previous studies mostly emphasize that a number of factors contribute to an underreaction to the information which gives rise to the possibility of a post-earnings announcement drift (PEAD). Bird, Choi, and Yeung (2014) argue that it is the prevailing sentiment and uncertainty over the post-announcement period that plays a much more significant role in explaining PEAD. This thesis corroborates the results of Bird et al. (2014) and establishes that it is the change of emotions over the post-announcement period, rather than the level of emotions at the time of the announcement, that is more highly correlated with the movement in stock prices during this period. This is an important insight as it suggests that stock valuations through time are always at the mercy of influencing factors such as human emotions and market sentiment. If this is the case, then it throws into doubt whether markets are ever truly efficient.

Fifth, we believe that this study also has implications for practice and provides guidance to investment decision-making. If emotion can impact investment decisions and, by inference, asset prices, then this failure to incorporate the influence of emotions on asset prices offers investors an opportunity to exploit and gain profits from emotion-driven mispricing of assets. The previous literature suggests that the investment strategies based on emotions are very sensitive to transaction costs, and once reasonable transactions costs are taken into consideration, the strategy results in a negative return (Tetlock, Saar-Tsechansky, & Macskassy, 2008). In this thesis, we develop a profitable investment strategy that generates a significantly positive return even after considering above-average round-trip transaction costs.

Finally, our work provides new evidence on the relative importance of social and news media postings on financial markets. Traditional news media such as broadsheets have been a reliable source of information for investors. However, the past two decades have seen a rapid expansion of information platforms in social media. The percentage of adults who use social networking sites has risen from 5% in 2005 to 72% by March 2021[1]. Our results show that although traditional news media is still very important, social media also plays a contributing role.

1.4 Structure of the Thesis

In total, there are seven chapters in the thesis which includes three chapters where we report the findings of our empirical research targeted to address our research questions.

Chapter 2: This chapter reviews the previous empirical research on emotions and their impact on decision-making. It also reviews the difference between emotion and sentiment. It also reviews the relationship between emotions and their impact on financial markets, and the impact of different emotions on decision-making. The review of emotion literature in financial studies shows that there are research gaps in terms of emotions and their impact on investors' decision-making.

Chapter 3: Here we discuss the various sources of data, and outline the steps taken to cleanse the data. In addition, we outline the various empirical methods employed in our three empirical studies.

Chapter 4: In this chapter, we first address the main research question: "Do the emotions expressed in the social and news media affect the decision-making of investors?". The proposition is that the posting in the news and social media will proxy for the investor emotions and these emotions will affect their decision making, and so affect the way they value stocks and react to information flowing (i.e., earnings announcements) from the company. We use four positive (optimism, joy, trust, and love/hate), five negative (stress, gloom, conflict, fear, and

[1] https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/

anger) and one neutral (surprise) emotion in our analysis. We further aggregate emotions into i) aggregate_emotion, ii) aggregate positive, and iii) aggregate negative. Our results show that the aggregate_emotion has a significant impact on the decision-making of investors. When we decouple the aggregate_emotion and analyse the individual emotions, we find mixed results where some emotions significantly impact decision making while others have little to no impact. This is true for both positive and negative emotions. Our analysis has confirmed that emotions play an important role in determining the valuations placed on companies, part of which is due to the impact they have on how investors react to new information.

Chapter 5: In the previous chapter, we studied the impact of emotions on stock prices at the time of the earnings announcement. In this chapter, we study the impact of emotions on stock valuations over the subsequent 60 days. Post-earnings announcement drift, which was first identified over 40 years ago, seems to be as much alive today as it ever was. While numerous attempts have been made to explain its continued existence using firm or market level characteristics, we aim to look at the impact of emotions on this anomaly. As with the previous chapter, we start our analysis with looking at the impact of aggregate emotion over the subsequent 60 days after the earnings announcement and then we move our analysis towards individual emotions. Our results show that PEAD is influenced by the level of emotions that prevails during the post-announcement period.

Chapter 6: In this chapter, we focus on developing an investment strategy that exploits mispricings that are attributable to human emotions. Quite simply, our findings reported in Chapter 4 suggest that prevailing emotions might result in an underreaction to earnings announcements. In Chapter 5, we highlight that the path taken by emotions during the post-announcement period can influence the path taken by stock valuations during this period.

Putting these two findings together, we demonstrate how we can develop a highly profitable investment strategy which perhaps is the best demonstration of the role that emotions play in distorting stock valuations.

Chapter 7: This chapter provides the summary of our key findings and outlines the possibilities for future research.

Chapter 2: Literature Review

2.1 Background of Study

There has been a significant development in the field of neuroscience which suggests that human economic behaviour is strongly influenced by finely tuned affective processes operated by the brain (Camerer, Loewenstein, & Prelec, 2005; Elster, 1998; Loewenstein, 2000). Emotion, as a major part of our affective processes, guides the incoming information processing (Gasper & Clore, 2002) and creates a significant impact on the economic decision-making of individuals (Camerer et al., 2005; Loewenstein, 2000). One important piece of information in the field of finance is earning announcements. Prior research has reported that several firm-specific characteristics such as transaction cost (Bhushan, 1994), options (Roll, Schwartz, & Subrahmanyam, 2009), trading volume (Chae, 2005), market capitalization (Poshakwale & Theobald, 2004), liquidity (Chordia, Goyal, Sadka, Sadka, & Shivakumar, 2009), and growth/value stocks (Chan & Lakonishok, 2004) have been found to affect the market reaction to earning announcements.

While most of the prior studies have concentrated on the firm-specific proxies to explain the price reaction to the earnings announcement, there exists scant literature that explains the contribution of emotions in shaping the price of a firm's shares. One of the major issues faced by academics while creating a link between investor emotions and asset pricing is finding an appropriate proxy to measure emotions. Some studies have tried to explain the relationship between emotions and financial market reactions using indirect proxies (factors that are known or assumed to induce a positive or negative emotion). For example, academics have used sunshine (Hirshleifer & Shumway, 2003), consumer confidence index (Fisher & Statman, 2003), daylight (Kamstra, Kramer, & Levi, 2003), nonsecular holidays (Frieder &

Subrahmanyam, 2004), sports events (Edmans, Garcia, & Norli, 2007), aviation disasters (Kaplanski & Levy, 2010), world value survey (Pevzner, Xie, & Xin, 2015), and air pollution (An, Wang, Pan, Guo, & Sun, 2018) as the proxies for investor emotion (mainly sentiment). However, the use of indirect proxies for investor emotions leaves such empirical studies open to the criticism of producing spurious results (Duxbury, Gärling, Gamble, & Klass, 2020). For example, the use of daylight as a proxy for investor emotion was challenged by Jacobsen and Marquering (2008). In another study, Wang and Markellos (2018) questioned the link between market returns and the emotion proxy generated by sports events. Furthermore, studies usually use the term sentiment and emotions interchangeably (e.g., Griffith et al., 2019). This is not true as there is a difference between sentiment and emotions. For example, Kumar, Ekbal, Kawahra, and Kurohashi (2019) argues that emotions are brief episodes and are shorter in length, whereas sentiment is formed and retained for a longer period.

In order to address the issue of indirect proxies for emotions, more precise and direct measures of emotions have been developed by using advanced textual content analysis of news and social media paired with extensive field-specific dictionaries (Griffith et al., 2019). As most human emotions are the outcomes of social and interpersonal communication (Andersen & Guerrero, 1996), the news and social media postings can be used as a direct proxy for human emotions (Kijkasiwat, 2021). By applying semantics to the social and news media postings, researchers have been able to provide a gauge of human emotion and how the emotions can impact financial markets (Antweiler & Frank, 2004; Chen, De, Hu, & Hwang, 2014; Karampatsas et al., 2018). However, most studies dealing with textual analysis are limited by a small sample size and they fail to distinguish between whether the emotions generated from the news media are dominant or one generated from the social media (Beckers, 2018). Furthermore, very little empirical research has been conducted to show that investor emotions (which are proxied by the news and social media postings) affect securities valuations (Griffith et al., 2019).

We are using a standardized database of emotions generated by scanning the news and social media. The Thomson Reuters MarketPsych Indices (TRMI) surveys the words used in social and news media listings relating to each company and calculates on a minute-by-minute basis the score for ten different measures of emotions from 1998 to 2017. We demonstrate that news and social media emotion measures are not only influential in shaping share price directly but have the potential to impact valuation indirectly by affecting the sensitivity of the investors' response to new information. For example, suppose that the postings in the media have a gloomy tone at a point in time. In that case, it should translate into a lower market valuation and a more negative response to bad news, and a less positive reaction to good news. In short, we believe that the emotional tone of the postings can affect how market prices are impacted both directly (direct channel) and by way of the investor's reaction to the news.

We will address four particular questions in the rest of the chapter: i) What are emotions? ii) Difference between sentiment and emotions iii) Do emotions impact human behaviour? and, iv) Impact of emotions in financial decision-making.

2.2 What are Emotions?

As the focus of our research is on emotions, we will start by addressing what we mean by this term. A person can experience a wide range of emotions including rage, hope, embarrassment, bliss, horror, and so on. So, it is not surprising that philosophers, psychologists, and other researchers have no exact definition of emotions. In the history of psychological literature, emotions have been defined in a number of different ways (Elster, 1998). For example, Kleinginna and Kleinginna (1981) conducted a systematic literature review and compiled a list of 92 different definitions of emotions falling into 11 categories based on theoretical issues or emotional phenomena. Similar to the psychological literature, we see a substantial debate in the business literature about how emotions should be studied and examined in relation to business studies (Plutchik, 1980, 1994). Although different psychologists have different definitions of emotions, the American Psychological Association defined 'emotion' as 'A complex pattern of changes, including physiological arousal, feelings, cognitive processes, and behavioural reactions, made in response to a situation perceived to be personally significant. The specific quality of the emotion (e.g., fear, shame) is determined by the specific significance of the event[2]". It is safe to say that emotions are complex psychological states and hate, happiness, optimism, joy are few examples of emotions.

While philosophers and psychologists are yet to come to a common definition of emotions, there is an agreement on certain characteristics of emotions. First, emotions are acute and are relatively short experiences that can influence the behaviour of an individual (Brosch, Scherer, Grandjean, & Sander, 2013; Scherer, 2005). For example, Young (1943) stated that emotion can be defined as an acute disturbance of the individual as a whole that is psychological in origin and can impact behaviour. Kemper (1978) emphasized the short-term nature of emotions, contending that Emotions are positive or negative short-term evaluative responses. Clore, Schwarz, and Conway (1994) defined emotions as intense and short-lived phenomena that usually have clear cognitive content that is accessible to the individual experiencing the emotion. Yuan and Dennis (2014) also argue that emotions are short-lived and can be defined as subjective reactions that are linked to personal goals or needs towards one's self or others

2 https://dictionary.apa.org/emotion

and are usually triggered by situational events in a person's environment. For example, emotions are about someone (e.g., you are angry with your partner), or emotions are about something (e.g., you are happy to hear a particular piece of news). Emotions are not everlasting -- once the stimulus that triggered an emotion disappears, the emotion itself will also gradually disappear (Andrade & Ariely, 2009). This unique characteristic differentiates emotions from other varieties of affects such as moods which generally span over a longer period.

The second important characteristic of emotions is that they are often aroused by external stimuli (e.g., news) and are usually directed towards a particular stimulus in the environment by which they have been aroused (Plutchik, 1980). Fear (or optimism) is an emotion that can be generated by the thought of what may happen (Elster, 1998). A person might read good or bad news (external stimuli) about a company, and this may lead to the arousal of optimism or fear which is directed towards the potential price increase or drop of the company's stock. For example, on 29th July 2019, Elon Musk, the mind behind Tesla and one of the richest person in the world, tweeted about Tesla's solar roof production. It created optimism about the prospects of the company in investors' minds and Tesla's stock closed at 3% higher than the opening price that day. Similarly, on 2nd May 2020, Musk tweeted that *"Tesla's stock price is too high imo"*[3], triggering a massive wave of fear among investors, leading to Tesla's stock price closing at 10% lower than the previous trading day[4]. Although both tweets were not backed by sound technical financial analysis, investors reacted to the emotions that were generated by the external stimuli (tweets/news). This suggests that emotions also generate a reaction to the perception of events (Clore, Ortony, & Foss, 1987). Additionally, emotions are also cognitively impenetrable. That

3 https://twitter.com/elonmusk/status/1256239815256797184?lang=en
[4] https://www.vox.com/recode/22464702/regulators-sec-elon-musk-tesla-tweets

is, if there is an event that is of concern to someone, a person cannot simply choose to have emotions or be devoid of emotion (Frijda, 1986).

Third, emotions are deeply rooted in social interactions and play a significant role in influencing a person’s behaviour (Williamson, 2002). Wickens and Meyer (1961) defined the relationship between emotions and behaviour as "[Emotions are] a form of responding, characterized by high levels of psychological activation, which often results in disruption of the usual patterns of behavior" (as cited in (Kleinginna & Kleinginna, 1981), pp. 368). There is evidence to suggest that emotions such as joy or anger act as a mental reaction which, in turn, plays a major role in the behaviour of an individual (Barbalet, 1999). For example, Bartlett and DeSteno (2006) studied the impact of positive emotions (e.g., gratitude) on human behaviour in two different studies/experiments. Both studies concluded that gratitude plays an important role in facilitating helping behaviour and the subjects showed a helping behaviour even if it was costly for them to help. Although emotions are acute and short-lived, their impact on human behaviour outlives the emotion itself (Andrade & Ariely, 2009). Like positive emotions, humans also experience negative emotions and if they are directed towards a company, they can create avoidance behaviour towards that company (Romani, Grappi, & Dalli, 2012).

In addition to characteristics, the emotion can be conceptualised by using the two dominant approaches (Calvo & Mac Kim, 2013; Russell, 1980). The first is the classic approach in which emotional states such as joy, sadness and anger etc. are considered (Bollen et al., 2011; Risius, Akolk, & Beck, 2015). The other approach is the dimensional model in which the emotion has two dimensions (Smailović, Grčar, Lavrač, & Žnidaršič, 2014). The first dimension is the valence dimension that 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). The second dimension of emotion is related to low or high arousal (Russell, 1980, 2003). Calvo and Mac Kim (2013) states that neither of the two approaches is more or less correct, and plotting the emotional states onto the dimensional model should be pretty straightforward. For example, the "calm" emotional state would be considered as having neutral valence and low arousal (Russell, 2003).

2.3 Difference Between Sentiment and Emotion

At this point, it is important to make the distinction between the concept of emotion and sentiment. This lack of differentiation not only leads to inconsistency in terminology usage but also makes the subtleties and nuances expressed by these terms difficult to understand (Munezero, Montero, Sutinen, & Pajunen, 2014). These terms are often erroneously used interchangeably in the economics/finance literature (e.g., Griffith et al., 2019). A popular psychology website defines sentiment as "a disposition or a tendency to experience a particular type of conscious state, but it is not innate like an instinct or emotion. It is a product of development, an acquired course of experiences"[5]. Munezero et al. (2014) stated that sentiment is an enduring attitude and is a permanent part of our mental structure. It makes for greater consistency of conduct and it leads to behaviour that can be predicted once the sentiment is known. For instance, a person who has a sentiment for sports, while taking a newspaper, will turn to the sports columns whether or not he is experiencing a happy or sad emotion. Another person loving movies will turn to the entertainment columns regardless of the emotion that person is experiencing at the moment. Thus, as compared to emotions, sentiment is present at all times and is a permanent state of mental organisation. Sailunaz and Alhajj (2019) argued that

[5] https://www.psychologydiscussion.net/

although sentiment and emotions are often considered replaceable terms, but sentiment represents a more general idea whereas emotions are short feelings or reactions that people have on a certain event. Similarly, Kumar et al. (2019) argued that emotions are brief episodes and are shorter in length, whereas sentiment is formed and retained for a longer period.

There are a number of studies that all use different proxies of sentiment to determine its impact on the stock market. The measure of sentiment is difficult and literature has proposed different sentiment proxies (Qiu & Welch, 2004). In dealing with investor sentiment three branches of literature emerged: i) articles that use investor surveys as the proxy for sentiment (e.g., Greenwood & Shleifer, 2014), ii) articles that use market and economic variables as proxies for sentiment (e.g., Baker & Wurgler, 2006), and iii) articles that use textual data as a proxy for sentiment (e.g.,Garcia, 2013).

Although Neal and Wheatley (1998) started by measuring investor sentiment proxied by three market variables. The most notable example of sentiment is the one by Baker and Wurgler (2006) (B&W) which utilises five financial metrics; the value-weighted dividend premium, the first-day returns on initial public offerings (IPOs), IPO volume, the closed-end fund discount, and the equity share in new issues. Similarly, Bathia and Bredin (2013) used a variety of market-related proxies, including equity put-call ratio, closed-end equity fund discount and equity fund flow. Shumway (2010) used economic variables as a proxy for sentiment. Fisher and Statman (2003), and similarly Schmeling (2009), examine the relationship between consumer confidence survey responses and stock returns. Then there are studies like Brown and Cliff (2004), Klein and Zwergel (2006), Schmeling (2007), Hengelbrock et al. (2011) and Lux (2011) that use investment survey data on sentiment. Then some studies use textual data as a proxy of sentiment (e.g., Da et al., 2015; Garcia, 2013). All of the studies use different proxies to measure sentiment.

Commenting on sentiment in financial studies, Bormann (2013) argued that a sentiment index can be any kind of available data as long as someone is convinced that these data depict the market sentiment as there is no official definition. However, Finter, Niessen-Ruenzi, and Ruenzi (2012) argued that all the proxies of sentiment presented in the literature e.g., market, economic and emotion, capture some aspect of sentiment. Similarly, Sibley, Wang, Xing, and Zhang (2016) argued that sentiment is an umbrella term that is composed of more than five components as defined by B&W. They suggested that approximately 63% of the total variations in the sentiment index can be attributed to the 13 different economic variables such as the T-bill rate and the market liquidity risk factor. Kumar et al. (2019) in their study argued that although sentiment and emotion are not the same, in reality, emotion is a part of the sentiment.

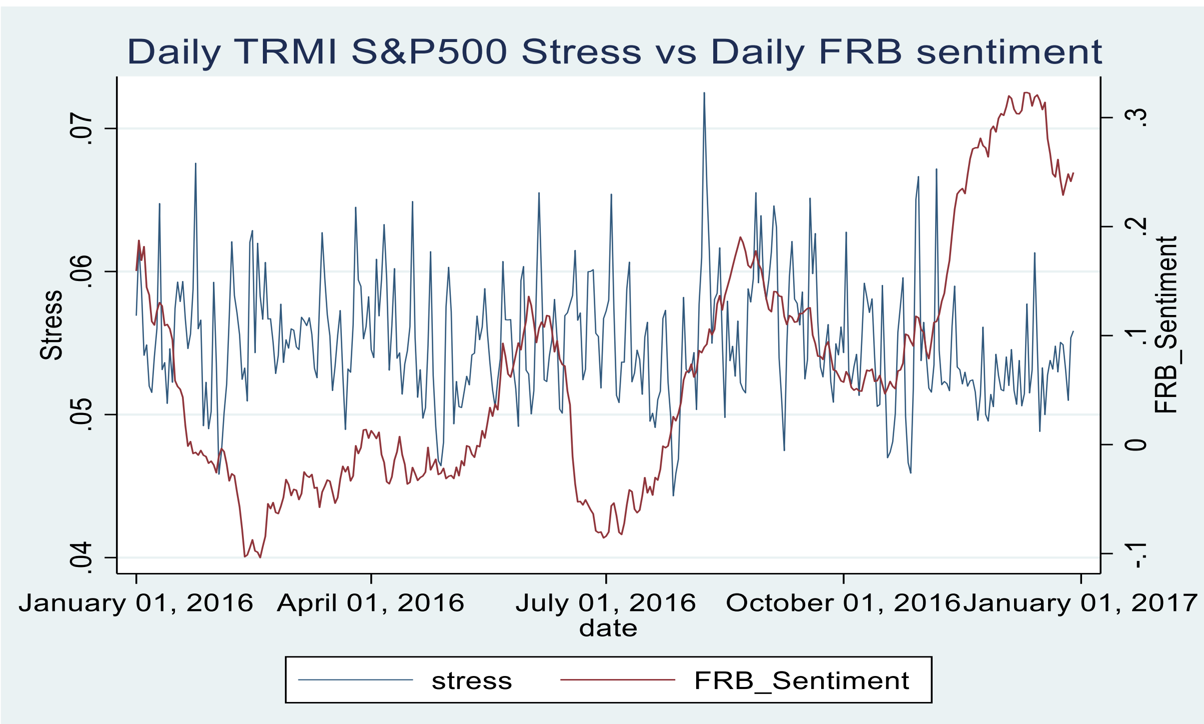
As discussed above that although emotions are a part of sentiment, the main difference between both of them is that emotions are brief episodes of behavioural changes, whereas, sentiment has been found to form and be held for a longer period and is more stable and dispositional than emotions (Munezero et al., 2014). To supplement the findings from previous studies that are discussed above, we did some empirical analysis and concluded that there is a difference between emotions and sentiment. Figure 1.1 shows the time-series graph of the daily News Sentiment Index which is calculated by the Federal Reserve Bank of San Francisco[6](FRB) and the daily Stress calculated by Thomson Reuters MarketPsych Indices (TRMI) at the market level (S&P500) for the year 2016. There are two implications that we take from this information: (i) We can see that sentiment forms for a longer period and we see a trend in one direction before reversing. Yes, there are short oscillations around a long-term trend in the sentiment index, but they can be because of emotions or some other market or economic components (e.g., close-end

[6] https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/

fund, T-bill rate) that sentiment is composed of. (ii) If we look at the emotion of STRESS[7] at the market level for S&P500, we see that it spikes in one direction which quickly reverses. These findings support the argument by (Munezero et al., 2014) that emotions are brief episodes whereas sentiment is much more permanent.

Figure 1.1: Time-series of Daily Sentiment vs Emotion at Market Level

The graph shows the time-series of stress and sentiment for 2016 for the US market. The blue line in the graph shows the daily value of Stress emotion that is calculated on the market level i.e., S&P500. The red line shows the daily News Sentiment Index which is calculated by the Federal Reserve Bank of San Francisco (FRB).



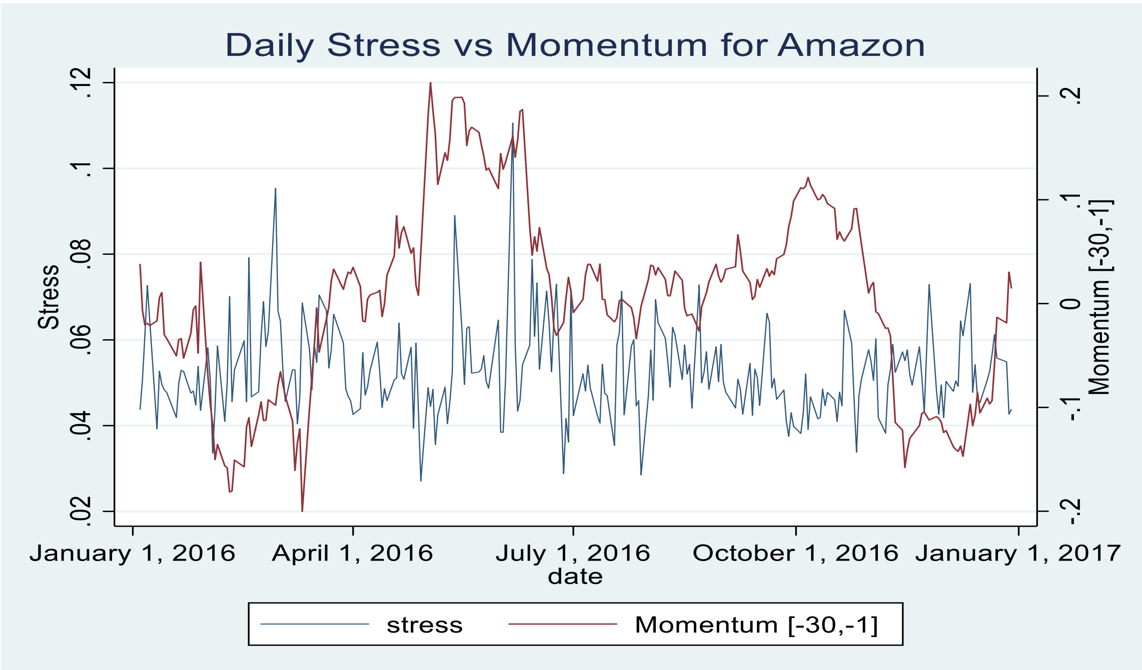
As figure 1.1 shows the time-series analysis of sentiment and emotions (stress in this case) at the market level, we further probe the difference by presenting in figure 1.2, the time-series of sentiment and emotion as measured at the firm level. The proxy for the firm (Amazon in this

7 We did the analysis for all the emotions with sentiment. The results of other emotions are quantitatively similar, and graphs would be available on request.

case[8]) sentiment is momentum (-30, -1) whereas the proxy for firm emotion is the TRMI emotion index. The results are almost similar to what we see in figure 1.1.

Figure 1.2: Time-series of Daily Sentiment vs Emotion at Firm Level

The graph shows the time-series of stress and sentiment for 2016 for the US market. The blue line in the graph shows the daily value of Stress emotion that is calculated on the firm level i.e., Amazon in this case. The red line shows the daily momentum (-30, -1) as a proxy for sentiment of Amazon.



To further shed light on the relationship between sentiment and emotion, we look at the correlation between sentiment and emotions. Table 1.1 shows the correlation between daily TRMI emotion indices with three different daily sentiment indices. The first column shows the correlation between ten individual emotion indices, three aggregate emotion indices at the market level and the daily Sentiment index from the FRB's website. The results show that there

8 We did the same analysis for top 20 firms (based on their market cap.) listed on the S&P500. To save the space, we have only presented result for one firm and one emotion. The results for other firms and emotions are quantitatively similar and will be provided on request.

is a very small correlation between emotions and sentiment, with the biggest correlation being 0.3873 for individual emotions and 0.4722 for aggregate emotions. This suggests that emotion is only one of several factors that contribute to sentiment. We also calculated the momentum (-30, -1) for each firm listed on the S&P500 and used it as a proxy for investor sentiment at the firm level. The second column of table 1.1 shows the correlation between momentum and emotions at the firm level.

The correlation between momentum and emotions seems to be very small. Finally, to find the correlation between sentiment that is calculated using the same database as emotions, we are using the data from TRMI that apart from calculating emotions, also calculates its own sentiment index. In the last column of Table 1.1, we show the average correlation between the firm sentiment and emotions for the top 20 companies (as per the market cap.) listed on the S&P500 index. Similar to the results of FRB sentiment, we see a small correlation between emotions and sentiment and emotion. This suggests that emotion is only one of several factors that contribute to sentiment.

Table 1.1: Correlation between Daily Sentiment Indices and Emotions

Emotions	FRB Sentiment	Momentum (-30, -1)	TRMI Sentiment
Optimism	0.3873	0.0469	0.5502
Joy	0.2228	0.0398	0.0596
Lovehate	0.3523	0.0506	0.1194
Trust	0.1782	0.0354	0.3377
Stress	-0.3154	-0.0367	-0.3629
Gloom	-0.1092	-0.0275	-0.3152
Fear	-0.0529	0.0023	-0.1156
Conflict	0.0535	-0.0219	-0.2856
Anger	0.1146	-0.0015	-0.2328
Surprise	0.1356	0.0211	0.0119
Agg_Pos	0.4722	0.0674	0.5590
Agg_Neg	-0.1229	-0.0345	-0.4984
Agg_Emotion	0.3510	0.0632	0.6516

The table shows the correlation between sentiment and emotions from 1998 to 2017. The first column shows the correlation between Daily FRB sentiment and emotions from athe TRMI index at the market level i.e., S&P500. The second column shows the average correlation between TRMI emotions and momentum (-30, -1) for the top 20 companies listed on S&P 500. The third column shows the average correlation between TRMI emotions and TRMI sentiment for the top 20 companies listed on S&P 500.

In summary, the concepts of sentiment and emotions have been used interchangeably in the literature. However, sentiments are differentiated from emotions by the duration in which they are experienced. Emotions are brief whereas sentiments have been found to form and be held for a longer period. Furthermore, sentiment is an umbrella term which is composed of many market and economic components other than emotions.

2.4 Do Emotions Impact Decision-Making?

The human brain is an arena where there is a constant battle between different forces: on one side of the continuum, we have reasoning, rationality, and deliberation while, on the other side, there is emotions, impulsiveness, and irrationality. The notion that human decision-making involves a constant battle between cognition and emotions has underpinned much research in psychology. We can trace this thinking back to the days of Plato, who divided the thought process into emotions (what we feel), cognition (what we know), and motivation (what we want). This was further developed by renowned philosophers like Rene Descartes in his final philosophical treatise, *The Passions of the Soul* and David Hume in one of his most important works, *A Treatise of Human Nature*.

For a long time, the human brain has been regarded as a "computer" where only cognition played a role in the decision-making process, and emotions were considered mere disturbances in the cognitive functioning of the brain (Miller, 2003). However, most theories of rational decision-making are implausible (Zeelenberg, Nelissen, Breugelmans, & Pieters, 2008). The notion that for every single decision a person makes in a fast-paced environment (e.g., financial markets), he/she should spend time and effort listing all the advantages and disadvantages, or undertake a cost and benefit analysis of all the alternatives to come to a final rational decision, is not only inefficient but is also at odds with introspection (Fenton-O'Creevy, Soane, Nicholson, & Willman, 2011). This can be attributed to the fact that we are limited by the time that is available to be spent on every decision that we make. Simon (1955) suggested that our rational decision-making capabilities are bounded by our cognitive capacities and emotions can aid decision-making by restricting the range of options to be contemplated in order to help decision-makers to focus on the critical aspects of the environment (Brosch et al., 2013). Kaufman (1999) suggested that emotion should not be viewed as an alternative to the rational expectation framework; rather, emotion's purpose is to contribute to bounded rationality. Phelps (2006) did a major review of the relationship between emotion and decision-making and concluded that along with cognition, emotions also play a significant role in the decision-making process.

We see several studies in the Psychology literature arguing that emotions have a core role in decision-making. For example, Dienstbier and Munter (1971) sought to determine the impact of guilt on students. Their study comprised two groups of students. The students were given a chance to cheat on a test that would eventually have an impact on their grades. One group of students were unwittingly given a tranquilizer that would block the generation of emotions in them. The authors posited that if emotions such as guilt were suppressed, they would decide to cheat in the test. Dienstbier and Munter (1971) reported that students who were given the tranquilizer cheated more in their test compared to those who were not given the tranquilizer. Isen, Daubman, and Nowicki (1987) conducted an experiment where participants were asked to perform two tasks that required creative ingenuity. To invoke positive emotions, they showed a two-minute comedy or gave a small bag of candy to participants before the problem-solving tasks. They found that positive emotions improved the performance of the individuals. Henrich et al. (2005) conducted a neuroeconomic experiment which indicated that when individuals perceived an offer as being unfair, this would generate feelings of anger and lead to emotionally driven decision-making. Although, on a purely cognitive basis, an acceptance of the offer would have yielded more benefit to the recipient of the proposal than a rejection of the offer, the study found that people were still inclined to reject the offer as a result of feeling wronged.

Economists have named the phenomenon of foregoing self-gain in the interest of the group as altruistic punishment. Fehr and Gächter (2002) showed that altruistic punishment may be applied by groups to keep the free-rider in check. They concluded that even though altruistic punishment involved financial loss, it was still perceived as satisfying, demonstrating that emotional responses may, at times, override cognitive decision-making. Rowe, Hirsh, and Anderson (2007) also found that positive emotions enhance the ability of a person to process information. Their study indicated that people experiencing positive emotions had a higher probability to solve unusual word association puzzles compared to people with negative or neutral emotions.

In the area of consumer behaviour and marketing, customer emotion is of paramount importance (Pham, 2004; Westbrook & Oliver, 1991). Several studies demonstrate that emotions play an important role in the decision-making process and empirically find that there is a direct impact of customer emotion on customer satisfaction (Oliver, 1993; Westbrook, 1987). For example, Raghunathan, Pham, and Corfman (2006) found that anxiety, which is associated with uncertainty and low control, led consumers to prefer safer options. Similarly, Kim, Park, and Schwarz (2010) showed that distinct emotions can influence the way consumers evaluate a product. They found that when consumers felt excited (as opposed to calm), they preferred adventurous (versus serene) product appeals. This shows an emotion-congruency effect: that is, when the emotional appraisal matched the product appeal, consumers expected the product to deliver what it promised. In another study, Maheswaran and Chen (2006) found that feelings of sadness have an impact on consumers when they are evaluating any product.

There is another stream of research that establishes how emotions guide information processing in individuals (Gasper & Clore, 2002). Biss and Hasher (2011) conducted a study and concluded that positive emotions broaden the attention of individuals that can impact the subsequent decision-making performance. Tiedens and Linton (2001), while analysing the impact of emotions on subsequent information processing and its accuracy, argued that positive emotions such as hope or joy, and negative emotions such as fear, can impact the information processing ability of an individual. They concluded that emotions related with uncertainty lead the individuals to contemplate more on the information and its accuracy in order to be more convinced about their decisions. However, the opposite is true for emotions that are related to certainty, where individuals felt confident about their decisions because of their prevailing emotions. Agrawal and Duhachek (2010) suggested that negative emotions such as guilt or stress influence decision-making. They argued that when the individuals experiencing negative incidental emotions receive positive information or a positive message, they ignore the positive attributes of the information/message and try to minimize the impact of that information. De Mello, MacInnis, and Stewart (2007) suggest that emotions can also affect information processing when the emotion is positive in valence, but under threat. They showed that when feelings of hope were threatened, individuals engaged in biased forms of information processing to restore their confidence and loss of control. In another study, Agrawal, Han, and Duhachek (2013) concluded that individuals experiencing negative emotions, such as anger, were more likely to reject any information that was not in line with their prior preference. For example, if an individual was expecting negative news about something and encountered positive news instead, the individual would be inclined to reject this because of prevailing negative emotions.

2.4.1 Impact of Different Emotions on Decision Making

Emotion is a very complicated, multidimensional characteristic which reflects the personality and behavioural traits of humans. In their daily life, people express their emotions on different issues, events, persons, environments, and even every little thing surrounding them. Emotions are regarded as intense and short-lived phenomena that most of the time have a clear cognitive content which is available to the person experiencing them (Clore et al., 1994). Literature suggests that emotions can be categorized on the basis of two dimensions (Russell, 1980). The first dimension is the valence which can be divided into positive and negative valence. People most of the time try to avoid the emotions with negative valence, whereas they actively pursue positive valence emotions (Sambrano, Masip, & Blandón-Gitlin, 2021). The second dimension is arousal which depicts the readiness with which a person would attend to the external stimuli. Both anger and sadness are negative emotions, but sadness is a low arousal emotion whereas anger is a high arousal emotion. The notion that a person experiencing sadness reacts to a situation differently as compared to a person experiencing anger has received support for empirical studies (e.g., Tiedens & Linton, 2001). For example, when a person is angry, they are in a reactive state and would believe that they can fix the situation if they take a swift action, whereas, sadness would lead a person to use a systematic and analytic-type processing style to evaluate how to improve the situation in the best possible way (Sambrano et al., 2021).

Numerous previous studies exploring the impact of emotions on decision-making focused on examining the impact of overall positive and negative emotions on decision-making processes, considering emotions as unidimensional and bipolar (e.g., positive or negative) constructs (Clore et al., 1994; Raghunathan & Corfman, 2004). While many studies bundle all emotions with positive valence in one group and negative emotions in another group, there are some studies which establish that emotions within the same valence group might have a different impact on decision making. For example, as discussed earlier, anger and sadness are emotions that fall under the banner of negative valence, but individually can have a different impact on the decision-making process of an individual because of the readiness (i.e., arousal dimension) with which a person experiencing these emotions would react (Angie, Connelly, Waples, & Kligyte, 2011; Lench, Flores, & Bench, 2011).

In addition to valence-arousal theory, Schwarz (2011), presented a "feeling-as-information" theory which argues that emotions with the same valence can have different effects on cognition. Both fear and anger fall under the same negative valence category, but their appraisal tendencies are opposite from one another, hence, they have a different impact on the decision-making of individuals (Lerner & Tiedens, 2006). When individuals experience either fear or anger, they have a different assessment of the future events. For example, when individuals experience the emotion of fear, they believe that there are more chances that a risky event will occur, whereas, people who experience anger, behave the opposite way. Smith and Ellsworth (1985) argued that the difference between reaction to fear and anger was because of the certainty and control, as a sense of situational control and uncertainty defines fear, a sense of individual control and certainty defines anger. In another study, Lerner and Keltner (2001), while studying both the naturally occurring and experimentally induced fear and anger, showed that fearful people expressed pessimistic risk estimates and risk-averse choices, and angry people expressed optimistic risk estimates and risk-seeking choices. Lerner, Li, and Weber (2013) argued that while both sadness and anger are negative emotions, their impact on financial decisions is different. Griffith et al. (2019) studied the impact of three different negative emotions (fear, stress, and gloom) on financial markets and concluded that while investors' fear and stress can be used to predict market return, gloom seems to play no role in predicting the market return.

Schwarz (2011) argued that not only can emotions within the same valence dimension (i.e., positive or negative) have different effects on decision-making, but also emotions with different valence dimension can have similar effects on decision-making. For example, Lerner and Keltner (2001) argued that the risk perception of angry (negative valence) people is similar to that of people experiencing happy emotions (positive valence). In fact, similar to happiness, anger can enhance self-belief even though it is a negative emotion(Lerner & Keltner, 2001). Garg (2004) showed that both happy and angry individuals show a higher probability of positive future events as compared to negative events. Additionally, Sambrano et al. (2021) argued that similar to happiness, anger can also trigger a less pessimistic view of an event in an individual. Both anger and happiness can lead an individual to react to a situation without deeply analysing the environment. Hemenover and Zhang (2004) concluded that individuals experiencing anger behave similar to those experiencing optimism.

In summary, although it is appealing to consider all negative(positive) emotions under the valence approach will have a similar impact on the decision-making of individuals, a number of studies put a question mark on these assumptions. We not only see that emotions of the same valence have a different impact on decision making, but literature also establishes that the emotion of opposite valence might behave in a similar fashion. The most prominent emotion is anger which behaves as a positive emotion in many situations.

2.5 Emotions in Financial Decision-Making

In literature, we see studies that have tried to explain the relationship between emotion (predominantly sentiment) and financial markets. For example, De Long, Shleifer, Summers, and Waldmann (1990) found that stock prices diverge from fundamental values, and higher than expected return is earned because of the noise traders' sentiment. Barberis, Shleifer, and Vishny (1998) developed a model for investor sentiment and showed that it has an impact on asset pricing. Kamstra et al. (2003) studied the stock price returns of eight countries. They argued that the length of daylight (a proxy for sentiment) has a profound effect on people's mood and, in turn, people's moods are related to risk aversion. Kamstra et al. (2003) linked depression with stock returns and found a significant relationship between both. Hirshleifer and Shumway (2003) used sunshine as the proxy for investor emotions and concluded that it has an impact on the stock market. Cao and Wei (2005) argued that temperature has an impact on the emotional state of a person, and it can impact decision-making. They established that high temperatures can lead to higher or lower stock returns whereas lower temperatures only lead to higher stock returns.

Apart from weather-related proxies for emotion (sentiment), we see literature where certain events have been used as a proxy for investor sentiment. For example, Frieder and Subrahmanyam (2004) examined the U.S. equity market during nonsecular holidays such as St. Patrick's Day, the Jewish High Holy Days of Rosh Hashanah, and Yom Kippur as a proxy for investor sentiment. They selected these days because the U.S. equity market is open these days and the Jewish and Irish demography that celebrate these holidays are well settled in the United States. They found positive returns around St. Patrick's Day and Yom Kippur, and negative returns around Rosh Hashanah. In an innovative paper, Kaplanski and Levy (2010) studied the relation between the disasters in the aviation industry (a proxy for sentiment) and stock market response covering a period from 1950 to 2007. They found that whenever there is an aviation disaster, it is followed by negative returns in the market. They concluded that the disasters incite fear, nervousness, distress, and bad mood among investors, which leads to more pessimistic decision making and so ultimately drives down stock prices. Edmans et al. (2007) studied the international soccer results from 1973 to 2004. They used the results of the soccer games as the indirect proxy for investor mood (sentiment) and concluded that the stock market declined following a loss in the soccer match. An et al. (2018) conducted a study on China's weather and concluded that air quality can influence the stock market.

Other studies use different surveys as a market-level proxy for investor sentiment. Fisher and Statman (2003) used the consumer confidence index (CCI) of the University of Michigan as the proxy for investor sentiment and found that there is a significant relationship between the CCI and stock returns of Nasdaq and small-cap companies. They also found that there is no significant relationship between CCI and S&P 500 returns. Lemmon and Portniaguina (2006) used the CCI and Conference Board survey of consumer confidence as the proxy for investor sentiment, revealing that sentiment has the ability to forecast the stock returns of companies that have small capitalization and low institutional ownership. Schmeling (2009) also used the CCI as a proxy for individual investor sentiments in 18 countries. They reported an inverse relationship between sentiment and future stock returns. Livnat and Petrovits (2019), using the investor sentiment proxy developed by Baker and Wurgler (2006), found that sentiment does affect excess returns. In addition to sentiment, Bird et al. (2014) used implied volatility index (VIX) as the proxy for uncertainty and concluded that both sentiment and uncertainty play a role in shaping stock prices. Pevzner et al. (2015) examined the relationship between the level of trust in the country and investors' perception and utilization of information transmitted by the firm in the shape of earnings. They analysed the abnormal trading volume and abnormal stock return variance during the earnings announcement period in a large sample of firm-year observations across 25 countries (1995-2008) and found that both measures of investor reactions to earnings announcements are significantly higher in countries which have higher levels of societal trust. Based on responses to the World Value Survey, societal trust was captured and used as a proxy for emotion.

Although studies that use indirect proxies for emotions have tried to establish a link between emotions and stock valuations, they may have limitations. For example, Jacobsen and Marquering (2008) concluded that the findings reported in Kamstra et al. (2003), about the correlation between stock returns and emotional proxies related to weather, might be spurious. Jacobsen and Marquering (2008) also stated that it would be premature to conclude that weather-related emotional proxies have an impact on the decision-making of investors. They also questioned the argument by Cao and Wei (2005) that daylight causes a change in the mood of investors, and that it, therefore, has an impact on stock returns. In another study, Pinegar (2002) argued that "daylight saving" is not a robust proxy for investor sentiment and it is sensitive to outliers. Similarly, Daszyńska-Żygadło et al., (2014) argue that CCI may be a good proxy for consumer sentiments, however, not all consumers are investors. Hence, a consumer's willingness to spend does not necessarily translate into a willingness to invest.

2.5.1 Media as a proxy for emotions

Academics and researchers have used various ways to collect data on human emotions. For example, to collect data on human emotions related to specific places, Nold (2009) invited participants to walk in certain neighbourhoods wearing a GPS and a polygraph device, that would record the ups and downs of certain bodily reactions (such as the quantitative level of sweat) associated with locations. To refine what we can call “emotion data,” Nold organized interview sessions after each walk, during which participants would explain the reasons behind the bodily reactions measured by the device. The comments and personal stories by the participants gave some meaning to the polygraph’s quantitative measurements of the body’s reactions. Although this method has its advantage of being accurate, it has the biggest drawback of not being viable for a calculation of a very large sample size. This method was further used by Resch, Summa, Sagl, Zeile, and Exner (2015) at a larger scale, in which they used a combination of emotion-detecting wristbands and social media posts to detect emotions and reported a correlation between them.

As internet has evolved into content creation platform where people express their opinions and experiences, media has become a new *El Dorado* for researchers and companies that are looking to mine personal information (Caquard & Griffin, 2018). Most people now use media to interact with each other, get information or for work. Media can provide a good proxy of emotions as it has the ability to constantly capture communication between millions of individuals and large groups over long periods of time (Pellert, Lasser, Metzler, & Garcia, 2020). This communication data is very important for studying emotions, because emotions are not only internal experiences, but often social in nature: Humans communicate their emotions in either verbal or nonverbal ways, including written and spoken language, and other behaviours (Rimé, 2009). Data from media provide new opportunities to trace emotions and well-being of individuals and societies(Pellert et al., 2020).

As compared to other methods of collecting data on emotions, a key strength of using media to get data on emotions is that it is collected using strong computational approaches and it can aggregate emotion data at a large scale. Large media datasets that combine data from many individuals are particularly well suited to examine large group emotions at the level of populations (Pellert et al., 2020). For instance, Goldenberg, Garcia, Halperin, and Gross (2020) argued that social media has made it possible to study collective emotions, which emerge from large group of people responding to the same situation at proximate points in time.

There are studies that test the validity of media as a proxy for emotions by comparing it with the surveys conducted for collecting emotion data and show a high correlation between both. For example, De Choudhury, Counts, and Horvitz (2013), in a study used Twitter posts to quantify postpartum changes in 376 mothers along dimensions of social engagement, emotion, social network, and linguistic style. In their study, De Choudhury et al. (2013) concluded that social media posts can be used to predict depression (emotion) in mothers with an accuracy of 71%. Pellert et al. (2020) compared emotion metric derived from social media postings with self-reported emotions from the UK's YouGov survey. The YouGov survey is a large self-response survey that includes questions on respondent's feelings (including happiness, anger and sadness), the survey elicits over 2000 responses each week. Pellert et al. (2020) used the emotion data from the YouGov survey to corroborate the accuracy of the textual analysis derived emotions remeasure. The authors found a high correlation between the textual analysis-based measures of emotions and self-reported feelings of the YouGov. Adding further merit to these textual analysis derived emotions measures, Garcia et al. (2021) showed when combined with user demographic data, emotions derived from advanced text analysis methods provide an accurate gauge of emotions in the general population.

Furthermore, We see many instances where news or social media has been used as a proxy for specific emotions such as praise, acknowledgement, sympathy, trust and distrust (O. Oh, Agrawal, & Rao, 2013; Wu, 2019). Emotion proxies can range from simple words identified in texts such as social media posts, to self-reflections about the emotional dimensions associated with measurements of our bodily reactions to the environment, as illustrated in Nold (2009) work (Caquard & Griffin, 2018). However, there are studies (e.g., De Choudhury et al., 2013) which show that the media can be used as a proxy for emotions with good accuracy. In the later sections, we will discuss extent to which media has been used in disciplines such as finance and marketing as a proxy for emotions (sentiment).

2.5.2 Studies Using News Media as a Proxy for Emotions

The importance and structure of the news media are very different from social media as the writing in news media is finely crafted to enable the writer's and editor's style, views, or bias to be reflected into the final article. To see the impact of human emotions on stock price formation using the index-level sentiment from news media, Tetlock (2007) measured the pessimism at the index-level using *The Wall Street Journal*. He included articles from 1984 to 1999 in his study and concluded that the pessimism generated by news media depresses prices. Dougal, Engelberg, Garcia, and Parsons (2012) studied the impact of news media (specifically *The Wall Street Journal*) on the Dow Jones Industrial Average (DJIA) index and found that DJIA future returns can be predicted by the day the journalist's article is published as well as the day immediately following. Garcia (2013) studied the impact of index-level sentiment on asset prices. He calculated the frequency of positive and negative words appearing in *The New York Times* and used these as the proxy for sentiment, concluding that sentiment predicts stock returns during a recession. Uhl, Pedersen, and Malitius (2015) also concluded that sentiments generated by the news media influences stock market returns. Using the macro-economic news sentiment, they were able to establish stock returns even after adjusting for the transaction cost.

We also see studies that have used firm-level sentiment which is calculated from the news media. For example, W. S. Chan (2003) used the Dow Jones Interactive Publications Library to find past news (as a proxy for sentiment) on companies in newspapers, newswires, and periodicals. The author compared the stocks which had news coverage with stocks which had lacked news coverage and found a strong drift in the stocks with bad public news. Similarly, Tetlock et al. (2008) concentrated on the negative words for companies listed on the S&P 500 in *The Wall Street Journal* and Dow Jones News Service. They showed that negative words in the news about a firm lead to a low forecast for the firm's earnings. Leinweber and Sisk (2011) used the Thomson Reuters News Scope for 7000 U.S. stock and constructed news-driven portfolios. They found that apart from some mega-cap companies, it takes time for investors to respond to news. Using neural network textual analysis by Thomson Reuters to measure the 'tone' or 'sentiment' in the news stories for individual companies, Heston and Sinha (2017) showed that the daily news predicts the stock returns for one or two days.

2.5.3 Studies Using Social Media as a Proxy for Emotions

The internet has revolutionized the way financial trading is done. This has not only affected the way investors trade (e.g., online trading platforms) but has also changed the way investors consume information. Now, not only do the major news outlets make their material readily available online, there are also social media websites where investors can interact informally and share their financial views about companies. As compared to traditional media, social media now plays a major role in the decision-making of customers (Gao & Hitt, 2012). A study by

Greenwich Associates[9] that included 256 corporate and public pension funds, insurance companies, endowments, and foundations in the United States, Europe, and Asia reported that 48% of investors said that they did additional research on an industry or a topic based on the information they received from social media. Thirty-seven percent shared information they had received from social media with decision-makers while 34% said the information from social media impacted their investment decisions. This all shows the importance of social media in financial decision-making and it would be instructive to explore the extant research in this area.

Like the news media, studies involving social media can also be divided into index-level and firm-level studies. For index-level emotions, Bollen and Mao (2011) analysed the data from Twitter from February 28, 2008 to December 19, 2008 and concluded that feelings of calm and happiness can predict the DJIA returns. Zhang, Fuehres, and Gloor (2011) measured hope and fear using Twitter from March 30, 2009 to Sept 7, 2009 and concluded that they are significantly positively correlated with VIX and have a predictive power in showing how the market will react the next day. Da et al. (2015) used daily internet searches between 2004 and 2011 as a proxy for market-level investor sentiment, concluding that investor sentiment can predict an increase in volatility. Karagozoglu and Fabozzi (2017) studied the impact of volatility generated from social media between July 2, 2012, to April 11, 2016, and argued that market-level volatility created from social media can be used to build profitable investment strategies. Wu (2019) created an attention proxy using the StockTwits and concluded that new attention due to social media can generate positive cumulative abnormal returns.

We also see studies that deal with firm-level sentiment. For example, Tumarkin and Whitelaw (2001) examined the internet message board activity and stock returns for 73 companies

[9] https://www.greenwich.com/press-release/social-media-influencing-investment-decisions-global-institutions

between April 1999 and February 2000 and found that there was no abnormal return even after abnormal message board activity. Comparatively, Antweiler and Frank (2004) studied the impact of messages posted on Yahoo! Finance for 45 companies listed in the Dow Jones Industrial Average. They established that messages posted on social media have an ability to predict volatility and that disagreement between different contributors on social media results in an increase in the trading volume. Sul, Dennis, and Yuan (2014) analysed the tweets between March to October 2011 for S&P 500 companies, finding that the emotional valence (positive or negative) about a firm has a significant relationship with the firm's stock return. To find an attractive trading strategy using social media, Sun, Lachanski, and Fabozzi (2016) investigated StockTwits from 2011 to 2015 for S&P 500 companies and concluded that StockTwits can generate a profitable investment strategy.

2.6 Summary

We find strong support in the literature for the contention that emotions affect the decision-making of individuals. While one individual's emotions may simply impact their decision making, once aggregated across market participants, emotion-induced decisions can alter asset prices and move financial markets. The review of emotion literature in financial studies shows that there are research gaps in terms of emotions and their impact on investors' decision-making. First, we see that there are studies that use weather, aviation disasters, or CCI as proxies for emotions. Although these studies indicate that emotions do impact on decision-making, these are limited by the proxies employed. Second, these are market-level proxies of emotion that might not reflect the impact of emotions on individual companies. To overcome this limitation, we also see relatively new studies that use textual analysis to generate emotion proxies from either the news or social media. Third, as the process of textual analysis is complicated, studies conducting firm-level emotion analysis are often limited by small sample sizes (some limited to a handful of stocks) over a limited time frame. This might restrict their investment applicability. Fourth, most of the studies are limited to using sentiment index or they generalize the emotions into positive and negative emotions. This is potentially problematic since not all emotions are equal. For example, both fear and anger are negative emotions, but they may have a different impact on the decision-making process of the investor (Lerner & Keltner, 2001).

Chapter 3: Data and Methods

3.1 Introduction

As the literature has long suggested that emotions are a principal driver for important decisions, it is unsurprising that we have seen an increase in interest in understanding the role that emotions play in economic decisions (Lerner & Keltner, 2001; Smith & Lazarus, 1990). The first study that we conduct examines the linkages between the emotions generated by the news and social media, and their impact on investor decision making, particularly around the time of an earnings release. We find strong evidence that emotions transfer to investors and impact on their decision-making. In our second study, we examine the relationship between emotions and investment decisions over the period between quarterly earnings announcements. We find that over this period, it is the change in emotion that has the greatest influence on stock price movements. We conclude the thesis with a third study that uses the insights from the first and second studies to develop an investment strategy aimed at exploiting mispricings attributable to emotions. The fact that we can identify a strategy(ies) that generates exceptional returns suggests emotions play an important role in distorting security prices.

3.2 Description and Sources of Data

We use a multi-dimensional data set on companies included in the S&P 500 over a 20-year period. The data falls into two categories, financial and emotions, and is sourced from several data sets which are outlined below.

3.2.1 Financial Data

One important piece of information required to conduct the study is a measure of the unexpected component of earnings, which is calculated using actual earnings and financial analysts' forecasted earnings. This information was obtained from the Institutional Brokers' Estimate System (I/B/E/S) database. Since our studies are very sensitive to the time at which the information becomes available to investors, another key piece of information that was required for this study is the timing of the earnings announcement. The earnings announcement date is reported both in I/B/E/S and Compustat which occasionally are in conflict. In order to eliminate the errors in determining the date on which the earnings announcement is made, we follow the literature (Battalio & Mendenhall, 2005), and drop any observation in the sample where the difference between the I/B/E/S report date and the Compustat report date is more than one calendar day. Furthermore, consistent with previous studies, if an announcement is made on a non-trading day, we move the announcement date to the next trading day. We also eliminate those observations for which we do have the announcement date and/or we do not have the analysts' earnings forecast data.

We obtain the adjusted price, shares data, and other firm-level variables for companies listed on S&P 500 from the Center for Research in Security Prices (CRSP), sourced through Wharton Research Data Services (WRDS). We also require data on the Implied Volatility Index (VIX) which is from the Chicago Board Options Exchange (CBOE). Data on daily, monthly, and yearly risk-free rates are sourced from Kenneth R. French[10]. Consistent with the literature, we drop any observation for which we have any missing financial data and we also have winsorised the firm characteristics at the 1st and 99th percentiles. Winsorisation of the data is a common

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

practice among researchers and practitioners alike to reduce the impact of outliers in the data (Ghosh & Vogt, 2012). We also drop an observation if the stock price is less than $1. To eliminate the firms with low liquidity, we include only those firms which have a market (book) value greater than $5 million at the end of quarter "t-1".

3.2.2 Emotions Data

Our proxies for investor emotions have been created based on the Thomson Reuters MarketPsych Indices database, from which we source the data on 10 distinct emotions. Apart from being adopted by academics, the TRMI database for news and social media emotions is also used by funds managers, brokers, governments, and by banking professionals (Peterson, 2016). This data is largely used in the prediction of asset prices and economic activities at both the micro and macroeconomic level. Several studies have already confirmed the effectiveness and accuracy of this database. For example, Michaelides, Milidonis, Nishiotis, and Papakyriakou (2015) found that variation of the TRMI metrics matched the data of manually collected sovereign downgrade news. In a separate study, Michaelides, Milidonis, and Nishiotis (2019) confirm that the TRMI currency sentiment index is consistent with manually constructed FX currency-related news.

The biggest challenge in extracting emotions from news and social media is that there is a huge difference in terms of communication language/style used in both mediums. For example, someone who made a huge profit from a trade might colloquially post on social media that “That trade was the bomb!”. The reference to ‘bomb’ is not associated with war or violence; instead, this person is showing a positive emotion of joy because of a very successful trade (Peterson, 2016). The TRMI's advanced linguistic algorithm is able to accurately identify such lexical statements and can generate different emotion indices based on news and social media.

There are a number of different approaches in emotion's literature to capture emotions from the news and from social media. Generally, in sentiment literature, a lexical analysis called the "Bag of Words" technique is used. In the "Bag of Words" technique, all words are counted according to their frequency, and no additional grammatical or relational post-processing is performed[11]. Then a quantitative index is created by utilizing the sentiment dictionaries. There are several limitations when a purely lexical approach is used. The most common is that common lexical approaches are used to extract one-dimensional emotion (sentiment). Another weakness of this approach is insensitivity towards grammatical structures. TRMI overcame it by developing an exclusive lexical repository of both complex and simple words from the English language that can be of possible relevance to economists and investors.

As the new colloquial language keeps on entering social and news media regularly, the TRMI database keeps on updating the text analytics dictionaries on a regular basis. Another advantage of using the TRMI database is that it differentiates between business news and general chat regarding a company. Only articles that have relevance to business or investment activities are added in the construction of emotion indices.

TRMI is not only sensitive to the grammatical structure but also accounts for correlation among the words (Audrino & Tetereva, 2019). For example, if there is a tweet "I am enjoying my instant oats", the TRMI will not register it as a positive emotion towards the company selling

[11] For details on common textual analysis techniques, please refer to the work of other researchers such as Loughran & McDonald (2011, 2013).

instant oats. It will only count the reference towards the calculation of the emotion index if the tweet is about the financial news/discussion of a company.

Based on a set of more than 4000 variables (such as *AccountingBad*, *AccountingGood*, *Fear*, *Anger*, *Stress*, *Joy)*, the TRMI constructs its indices for various positive (e.g., optimism, joy, trust, and love/hate) and negative emotions (e.g., stress, gloom, fear, anger, and conflict) instead of one single sentiment index. Then, based on the tense, proximity, and many other multipliers, a numerical value is assigned to each variable. To better understand this procedure, let us look at the following example (tweet) from Peterson (2016).

Analysts expect Mattel to report much higher earnings next quarter.

The TRMI's exclusive software will perform the analysis in the following sequence.

1. The algorithm will first look for the entity reference of *"Mattel"* and associate it with its ticker symbol *MAT* in the database.
2. The word *"earnings"* will be linked to the variable *Earnings* in the database.
3. The word *"expect"* is identifying the sentence to be future-oriented, therefore the software will assign a future tense to the sentence.
4. Next, *"higher"* is an Up-Word. Therefore, the software will assign a positive value to this sentence.
5. In the sentence, the word *"higher"* is accompanied by another modifier word *"much"*, therefore, the value of *"higher"* will be multiplied by 2.
6. Finally, the word *"higher"* is associated with *"earnings"* because of its proximity.

The steps that are described above lead to a positive score of *EarningUpFuture* for the ticker *MAT*. Similar to this procedure, different emotions are calculated for each company. It is worth mentioning that a single piece of news can be attributed to different emotions. For example, the above example is regarding the variable *Earning*, however, it will also contribute towards the variable *Optimism*.

We include four positive emotions (optimism, joy, trust, and love/hate) and five negative emotions (stress, gloom, fear, conflict, and anger) in our studies. We also include 'surprise' which we classify as a neutral emotion in being neither positive nor negative. These emotions extend back to 1998 and construct three additional emotion measures, an aggregate positive emotion, an aggregate negative emotion, and an aggregate emotion that is based on all four positive and five negative emotions. One significant advantage of employing this unique dataset from a professional data provider is that it is free of the constraints of a limited type of media source, a limited number of assets, and short sample periods of other textual analysis derived data (Sun, Najand, & Shen, 2016).

TRMI data is obtained by scanning two million social media sites (e.g., Yahoo! Finance, Stocktwits, Blogger, Seeking Alpha, Google News)[12] and 50,000 professional news sites (e.g., *The Wall Street Journal*, *The New York Times*, and *The Financial Times*, etc.) to measure these emotions. As discussed earlier, each posting on each site is screened to determine that it has financial relevance to the company to which it relates. If it passes this filter, then the posting is processed using the TRMI's linguistic software to determine how much (if anything) it contributes to the score for each company in terms of the different measures of emotions. The result of this process is that we have a score for each of the 10 individual emotions calculated

[12] Thomson Reuters claims that the TRMI index covers the top 30% of all social media sources (Nooijen & Broda, 2016).

on a minute-by-minute basis for both the news and social media for the companies included in the S&P 500 index.

The TRMI S&P 500 emotion indices scores are either bipolar (-1 to 1) or unipolar (0 to 1). For example, ‘optimism’ is an example of a Bipolar index where a score of +1 indicates extreme optimism, while a score of -1 indicates extreme pessimism. Joy is an example of a Unipolar index which is positive with a score of +1 indicating extreme joy, while stress is an example of a Unipolar index that is a negative emotion with a score of +1 indicating extreme stress. Table 3.1 provides an overview of all the individual emotions and the scoring used in the study.

There are some instances when we must deal with the missing values of emotions, which occur when there is no observation at a particular time for a specific emotion because there are no conversations regarding a company at that time. This is different from a zero reading of emotion where people are neutrally disposed on a subject. Following Ryan and Giles (1999), we deal with missing values by carrying forward the previous observation. However, we only carry forward the previous score of emotion if it is within a 72-hour window. If we do not have any emotion score for more than 72 hours, we simply drop that observation from the data. For example, if at 4pm t-1 (the day before the earnings announcement) we do not have an emotion score, however, we do have an emotion score for 10am t-1, we will carry forward the score from 10am t-1 to 4pm t-1. Similarly, if at 4pm t-1 we do not have an emotion score and the last available emotion score is at 4pm t – 6, we will drop that observation because the emotion score does not qualify to be added into the data. By imposing this constraint, on average, we lose 50% of our quarterly sample.

Table 3.1: Summary of Emotions Used in the Study

Emotion	Description	Range
	Positive Emotions	
Optimism	Optimism, net of references to pessimism	-1 to +1
Joy	Happiness and affection	0 to 1
Trust	Trustworthiness, net of references connoting corruption	-1 to +1
Love/Hate	Love, net of references of hate	-1 to +1
	Negative Emotions	
Stress	Distress and danger	0 to 1
Gloom	Gloom and negative future outlook	0 to 1
Fear	Fear and anxiety	0 to 1
Anger	Anger and disgust	0 to 1
Conflict	Disagreement and swearing net of agreement and conciliation	-1 to +1
	Neutral Emotion	
Surprise	Unexpected events and surprise	0 to 1

As discussed earlier, we source nine different positive and negative emotions from TRMI. We calculate the aggregate emotion, and the aggregate positive and negative emotions based on a group of positive/negative emotions. For the aggregate positive emotion score of a firm 'i' on the day 't', we take the average score of optimism, joy, trust, and love/hate. We drop the observation if we have less than two positive emotions to make up the aggregate positive emotion. Similarly, for the aggregate negative emotion score of a firm 'i' on the day 't', we take the average score of stress, gloom, fear, anger, and conflict. We drop the observation if we have less than three negative emotions to make up the aggregate negative emotion. For aggregate emotion, we drop the observation if it has less than two positive and/or less than three negative emotions score for a firm 'i' on the day 't'.

For all our studies, we use the daily data (window length) which is updated on an hourly basis and represents the score over the previous 24 hours. For example, one series of TRMI scores for ‘optimism’ at 4pm on 11th January 2008 relates to the data collected between 4pm on January 10th, 2008, and 4pm on January 11th, 2008. The next set of scores for ‘optimism’ would be based on the data collected between 5pm on January 10th, 2008, and 5pm on January 11th, 2008. For our studies, we use the score for each particular emotion at 4pm each day.

3.3 Methods

In this section, we will discuss how we calculate the variables that we are going to use in each of our studies. We will also include a general discussion on the methods employed in the various studies. There are some variables that are common to all our studies while other variables are used only in specific studies.

3.3.1 Unexpected Earnings

The value of a firm is dependent on investor expectations of the future earnings generated by the firm and the risks attached to these earnings. In turn, these expectations are derived based on the information that is available to the investor. Undoubtedly, one of the most relevant sources of information in shaping these expectations is earnings announcements. At the time of the release, an investor will compare the earnings number just released with their expectations. If the number diverges from their expectations, then the potential is for the investor to revise their expectations of future earnings and so the valuation that they place on the firm. A similar process will be followed by other investors, and this will result in trading and the establishment of a new market price for the firm's shares. Therefore, investors are particularly interested when new earnings information becomes available as it has the potential to have a significant effect on stock prices (Ayers, Li, & Yeung, 2011; Zhang, 2006). The issue that we address in our studies is whether the way investors react to the information signals (e.g., earnings announcements) is influenced by the emotions expressed in the postings on social media and the news.

Central to our analysis is the unexpected component of the earnings announcement (i.e., earnings surprise). The two most common ways that are employed to find the earnings surprise are 1) the seasonal random walk method (Ayers et al., 2011; Chen, Lobo, & Zhang, 2017) and 2) analyst forecast based earnings surprise (Milian, 2015; B. Wang, Choi, & Siraj, 2018). Previous literature, such as the work of Doyle, Lundholm, and Soliman (2006) and Livnat and Mendenhall (2006), suggests that the analyst forecast-based earnings results in more persistent returns than those based on a seasonal random walk. Therefore, because of its more intuitive appeal and superior predictive power, we use forecast-based earnings surprise in our study. The unexpected earnings (UE) are measured as the difference between the actual earnings per share (EPS) and the median value of the latest consensus earnings estimate by analysts (Doyle et al., 2006).

Therefore, the Unexpected Earnings for a firm "i" is

$$Unexpected\ Earnings_i = Actual\ Earnings\ per\ Share_i - Latest\ Median\ Expected\ Earnings_i$$

where the expected earning is the latest median consensus earnings before the actual earnings announcement. Following the literature (Bird et al., 2014; Kaestner, 2006), the unexpected earnings are scaled by the absolute value of the actual EPS[13].

$$UE_i = \frac{Actual\ Earnings\ per\ Share_i - Latest\ Median\ Expected\ EPS_i}{Actual\ Earnings\ per\ Share_i} \quad \ldots \text{(Eq. 1)}$$

We scale the unexpected earnings to standardise the earnings surprise across our sample. We further divide our sample based on good and bad earnings news. Thus, we have Positive Unexpected Earnings (PUE) when the actual earnings per share are greater than the expected earnings. At the same time, we have Negative Unexpected Earnings (NUE) when the actual earnings per share are less than expected. Finally, there are some instances when the actual earnings per share are equal to the expected (i.e., no surprise), and in these cases, we place the observation in the PUE subsample.

3.3.2 Abnormal Returns

There are many firm and economy-specific events that can influence a firm's stock price including mergers and acquisitions (Mitchell, Pulvino, & Stafford, 2004), earnings announcements (Bird et al., 2014), and macroeconomic events (McQueen & Roley, 1993). In our study, the main event around which we examine the impact of emotions on stock prices is earnings announcements. We have selected this event because it provides an update on the piece of information that is fundamental to valuation and because it provides a large number of observations. For example, only a limited number of firms are involved with a merger or

[13] We also scale the unexpected earnings by price and by median consensus analysts forecast. However, the results are quantitatively similar.

acquisition in a fiscal year, while all S&P 500 companies are required to report on their earnings four times a year.

We study the behaviour of a firm's stock price at the time of the release of its earnings report. To analyse this, we need to identify the extent to which a firm's price moves around the time of an earnings announcement. Therefore, first, we define *"t0"* as the day of the earnings announcement whereas any day before the earnings announcement will be denoted by a negative sign, and any day after the announcement will be denoted by a positive sign. For example, a day before the announcement will be denoted as "t-1", whereas a day after the announcement will be denoted as "t+1". If the announcement is made on the weekend or a public holiday, we move the announcement day to the next working day, with t-1 and t+1 being adjusted accordingly.

In general, the price behaviour of any stock is measured in terms of the returns, which is defined as:

$$SR_{i,t} = \frac{P_{tN} - P_{tn}}{P_{tn}} \dots \text{(Eq. 2)}$$

where $SR_{i,t}$ is stock return at the time 't', for the company 'i', P_{tN} is the adjusted closing price at the end of the event window, and P_{tn} is the adjusted closing price at the start of the event window. We calculate the market return as follows:

$$IR_t = \frac{I_{tN} - I_{tn}}{I_{tn}} \dots \text{(Eq. 3)}$$

where IR_t is the Index return at the time 't' for the S&P 500 index. I_{tN} is the adjusted closing price at the end of the event window and I_{tn} is the adjusted closing price at the start of the event window.

Then we calculate the market-adjusted abnormal return as a measure of stocks performance against the market benchmark by subtracting the market returns from the stock returns. We calculate the abnormal return as follows:

$$AR_{i,t} = SR_{i,t} - IR_t \ldots \text{(Eq. 4)}$$

where $AR_{i,t}$ is abnormal return at the time 't', for the company 'i'. Following the literature, we aggregate the abnormal returns over the event window (MacKinlay, 1997). This aggregated measure is referred to as the cumulative abnormal return (CAR) and provides us with a measure of how the stock has performed over the event window.

The cumulative abnormal return (CAR) is calculated as follows:

$$CAR_{i(tn,tN)} = \sum_{t=t_n}^{tN} AR_{i,t} \ldots \text{(Eq. 5)}$$

We use the market model to obtain a second measure of cumulative abnormal returns. The market model specifies a linear relationship between the returns of the market and the returns of the stock. According to MacKinlay (1997), the market model removes the part of the company's return that relates to variations in the market, and enables us to identify the abnormal component of the return. Consistent with previous studies, we estimate the market model over the 252 trading days prior to the announcement (MacKinlay, 1997) and we use the following equation to estimate the market model:

$$E(R_{i,t}) = \alpha + \beta_1 IR_{i,t} + \varepsilon_{i,t} \ldots \text{(Eq. 6)}$$

where $IR_{i,t}$ is the S&P 500 return for period "t" and α and β are the coefficients that we determine by running an ordinary least square regression over the estimation window. We also calculate the market model abnormal return by finding the difference between the stock return and the expected return calculated using the market model.

$$MMAR_{i,t} = SR_{i,t} - E(R_{i,t}) \ldots \text{(Eq. 7)}$$

Similar to Eq. 5, we also calculate the CAR for the market model as follows:

$$MMCAR_{i(tn,tN)} = \sum_{t=t_n}^{tN} MMAR_{i,t} \ldots \text{(Eq. 8)}$$

where $MMCAR_{i(tn,tN)}$ is the market model cumulative abnormal return. In the next section, we will review the regression analysis used in our studies.

3.3.3 Regression Analysis

In the first two of the research chapters, we apply Ordinary Least-Squared Regression (OLS) to investigate the relationship between emotions and stock returns. In this section we generally provide some background to our use of OLS analysis, leaving the discussion of the specifics of the regression run until the appropriate chapter.

OLS regression is used when we want to predict a dependent variable from a number of independent variables. For example, the linear relationship between a dependent variable Y (house price) and an independent variable X (size of a house) can be explained by the following equation:

$$Y = \alpha + \beta_1 X + \varepsilon \quad \ldots \text{(Eq. 9)}$$

where α is the intercept of the line. It is a constant term and is a value at which the regression line crosses the y-axis on an XY-graph. β_1 is the slope of the line and ε is the error term that represents the margin of error within the OLS regression. Now, if we run regression analysis and get the following, Y = 50,000 + 7X, then if X is 3,000 square feet, then the house price will be Y = 50,000 + 7 * 3,000 = $71,000. However, some houses will sell for a higher price, and some will sell for a lower price for many other reasons (that we did not include in the model) apart from size. We can expand the eq (9) where we add more variables on which the price of a house can be dependent. By adding more consequential explanatory variables, the problem of omitted variable bias can be reduced. Multiple regression with *n* number of independent variables can be illustrated as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_n X_n + \varepsilon \quad \ldots \text{(Eq. 10)}$$

It is important to mention that the statistical aspects of multiple OLS regression are the same as those of simple OLS regression. In the above discussion, we have assumed that the error terms are independently distributed and are identical in a panel dataset. This ignores the panel attributes of the dataset and treats the error term as uncorrelated with independent variables. To address this, the fixed- or random-effect model can be used. Following the literature (Du, 2020), we conduct both the Breusch-Pagan Lagrange Multiplier test and the Hausman test. Based on the results of these tests[14], we use the fixed-effects model in our analysis. Gormley and Matsa (2014) suggest that while applying the fixed-effect model, the standard errors must be properly adjusted. Therefore, following the literature (Petersen, 2009), we cluster the standard error by firms.

3.3.4 Control Variables

We include numerous control variables in our study. These include firm size (Bernard & Thomas, 1989), earnings volatility and book-to-market (Hirshleifer, Lim, & Teoh, 2009), Friday (Hung, Li, & Wang, 2014), beta and loss (DeFond, Hung, & Trezevant, 2007), FQ4 (Sun, 2015),

[14] Results are not reported but are available on request.

VIX (Bird et al., 2014), and momentum (Boehmer & Wu, 2013; Ke & Ramalingegowda, 2005). We define each of the nine control variables as follows.

1. **Ln of Market Value (MV)**: Ln of Market Capitalization at the end of quarter t-1.

2. **Log (Book-to-Market):** The logarithm of book-to-market (BTM) ratio, calculated at the end of each June based on the book value of equity for the last fiscal year-end in the previous calendar year divided by the market value of equity for December of the previous calendar year.

3. **Beta**: Estimate on market returns in a market model regression for firms with daily returns in the 250 trading days before the earnings announcement. Observations which had less than 100 trading days for estimation were dropped.

4. **FQ4:** A dummy variable that takes the value of 1 if the announcement is of the fourth-fiscal quarter, otherwise its value is 0.

5. **Loss:** A dummy variable which takes the value of 1 if the I/B/E/S value of actual EPS is negative, otherwise its value is 0.

6. **Implied volatility index (VIX):** It is a measure used to track volatility on the S&P 500 index and is the most well-known volatility index on the markets.

7. **Friday**: A dummy variable that takes the value of 1 if the announcement was made on Friday, otherwise its value is 0.

8. **Evol:** Earnings volatility, calculated as the standard deviation during the preceding four years of the variations of quarterly earnings from one-year-ago earnings (minimum 4 observations required).

9. **Momentum:** Our measure of momentum is the abnormal return measured over the five trading days prior to the earnings announcement.

A particular issue with our analysis relates to the existence of a potential causality loop between emotion and returns. The inclusion of the momentum in our analysis serves to address a potential endogeneity issue (Leszczensky & Wolbring, 2019). We note that the inclusion of the momentum variable did not alter any of the results of the analysis. We, therefore, conclude that the endogenous relationship between emotions and stock returns did not influence our findings.

3.3.5 Portfolio Returns

In contrast to the first two research papers, the third concentrates on the identification of an investment strategy to exploit any mispricing opportunities attributable to emotions. This strategy will involve a set of rules that define when we acquire/sell short stocks, the weighting for these stocks, and when the initial transaction is reversed. In summary, the rules will determine the holding in both a long and a short portfolio.

We calculate the daily return for the stocks in our portfolios by applying the following equation:

$$SR_{i,t} = \frac{P_{t1} - P_{t0}}{P_{t0}} \dots \text{(Eq. 11)}$$

where $SR_{i,t}$ are stock returns at the time 't', for the company 'i', P_{t0} is the adjusted closing price of the previous trading day, and P_{t1} is the adjusted closing price of the current trading day.

Initially, we assume that the portfolios are rebalanced each day so that each stock has equal weight. Hence, we then proceed to calculate the daily returns for each portfolio by calculating the average return of each stock included in the portfolio on that day.

$$PR_{i,t} = 1 + \frac{\sum_{t=t_0}^{t1} SR_{i,t}}{\text{number of stocks at time "t"}} \quad \ldots \text{(Eq. 12)}$$

where $PR_{i,t}$ are portfolio returns at the time ‘t’, for portfolio ‘i’. For the short portfolio, we multiply $SR_{i,t}$ with -1.

3.3.6 Index Creation

For each portfolio strategy, we create an index that starts at 100 on 1st January 2003. Then the daily returns will determine the values that the various indices take through time. Based on the portfolio return on each day, that index will either increase or decrease depending on the return that is generated by the portfolio. For example, if the return on the portfolio on the first day is 10% (-10%) then the index will increase(decrease) to 110(90).

3.3.7 Annualised Returns

For each portfolio, we calculate the annualised portfolio returns as follows:

$$APR_{i,t} = (((IV_t \,/\, IV_{t-1}) \wedge (12 \,/\, n)) - 1) * 100 \ldots \text{(Eq. 13)}$$

where $APR_{i,t}$ is the annualised portfolio return for the portfolio “i” at the time “t”. IV_t is the index value at the end of 2017, whereas, $IV_{t-1} here$ is the index value at the beginning of 2003. n is the number of months from the beginning of 2003 to the end of 2017.

3.3.8 Weighted Returns on Long/Short Portfolio

Since the 1980s, institutional investors in the United States have frequently used long-short strategies. Long/short strategies provide for more opportunities, and, over the course of time, they have been adopted by many investors. Long/short strategies offer the potential to implement superior information more efficiently than long-only strategies (Grinold & Kahn, 2000). Following Peterson (2015) we calculate the weighted returns on the Long and the Short portfolios to calculate our return on the long/short portfolio. For every year, first, we calculate the weight of our long portfolio and our short portfolio. Then we simply multiply them to get the return on the long-short portfolio. By decomposing the long/short returns, we can identify the contribution of both the long and short portfolios in the overall returns.

Calculating Weights for Long = Value of Long / (Value of Long + Value of Short) … (Eq. 14)

Calculating Weights for Short = Value of Short / (Value of Long + Value of Short) … (Eq. 15)

Long/short return = (Weight of Long * Return of Long) + (Weight of Short * Return of Short) … (Eq. 16)

From Eq. 14(15) we calculate the weight of long(short), then using Eq. 16, we calculate the weighted return on our long-short portfolio.

3.3.9 Sharpe Ratio

We calculate the Sharpe ratio in order to compare the return on the various investment strategies on a risk-adjusted basis. Following the literature (Yang & Zhang, 2019), we use the average risk-free return during the sample period as the minimum acceptable return. We use the following equation to calculate the Sharpe ratio:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \quad \ldots \text{(Eq. 17)}$$

Here, Rp is the return on the portfolio, Rf is the risk-free rate and σp is the standard deviation of the portfolio's return. We report the annualized figures.

3.3.10 Look-Ahead Biases

One issue that we have to be aware of is the potential to build a look-ahead bias (Song, Liu, & Yang, 2017) into the investment strategies that we create. Therefore, we take the following steps:

1. In some strategies, we divide both the positive and negative unexpected earnings into above- and below-median at the time of the announcement. This involves us having a measure of the median value for both PUE and NUE. We avoid a look ahead bias by only using data from past announcements when specifying the median. Although we have data from January 1998, we do not start forming portfolios until January 2003 and so we have five years of data to calculate the initial medians with subsequent medians being determined using an expanding window.
2. In some strategies, we restrict our investments to stocks whose emotion scores fall into the bottom quartile. Hence, we need to know the breakpoint for the bottom quartile by emotion in order to implement the strategy. Again, we avoid the look-ahead bias by using the holdout period of five years to calculate the initial break point which we then update using an expanding window.
3. In some strategies, we use a trigger for selling stocks based on the standard deviation of an emotion score. Again, we need past data to determine this standard deviation which is another potential source of look-ahead bias. Having a five-year holding period provides the data to calculate the initial standard deviations which are then updated using an expanding window.
4. Another potential look-ahead bias is when a firm announces its earnings, but is dropped as we do not have the returns data for the full quarter because the firm gets delisted before the end of the quarter. To avoid this, we keep the firm quarter in the portfolio but follow the rules listed below
    i. It will be traded as normal (following the particular strategy) if the trigger for buying/selling comes before the delisting date.

ii. If there is no trigger before the delisting date, then we will reverse the trade on the date the firm gets delisted and will adjust the delist return in our portfolio.

3.4 Conclusion

We discussed in general terms the data and research methods employed in the three research studies reported in this thesis which focus on the relationship between emotions and company valuations. We maintained that emotions impact directly on stock returns and also indirectly via the influence that emotions have on how investors react to information signals. In order to capture the direct and indirect effects, we concentrated on evaluating the relationship around the time of an earnings announcement (first study) and then over the period after the announcement (second study). A general discussion of the data used in these first two studies and the regression analysis employed was included in this chapter. The third paper concentrates on how one might employ the insights provided by the first two research chapters to identify a profitable investment strategy. In this chapter, we also provided some background discussion relating to the formation of portfolios and how their performance is measured that is fundamental to the analysis undertaken in the third paper.

Chapter 4: Do Emotions Expressed in the News and Social Media Impact on Investor Behaviour?

4.1 Introduction

Amid the COVID-19 pandemic in 2020, global financial markets suffered massive falls and extreme volatility. During this tumultuous period, RavenPack, a data service that applies textual analysis to glean emotions from media postings to create emotion indices such as the fear index, was able to show an uncanny ability to predict returns.[15]

The idea that emotions can impact on how an individual makes choices is not new. Dating back to the 18th century, philosophers like Jeremy Bentham considered that the goal of individuals when making decisions is to maximise the quantum of their happiness (as measured by the sum of positive emotions and negative emotions) (Loewenstein, 2000). Yet twentieth-century neoclassical economists have largely ignored the role of emotions in determining utility, instead favouring a framework where individuals make rational decisions to maximise expected utility based on the probability of expected outcomes. However, the fact remains that we are all subject to a fluctuation of emotions, and so it is essential that we "understand what role emotion plays to have a complete theory of human rationality" (H. Simon, 1990), p. 29).

This is the challenge that we take up in this paper where we focus on how emotions engendered by social and news media impact on the valuation of a company's stock. We examine two channels through which emotion might influence stock valuation: a channel where the investor's state of mind, conditioned by emotions, directly impacts on the valuation they place on the

[15] More details on the performances of these indices to predict stock returns during the Covid-19 crisis can be found in the following website: (https://coronavirus.ravenpack.com/)

company, and a second channel where the emotions influence investor reaction to new information emanating from the company (in our case, earnings announcements).

Studies to date have mainly concentrated on a single 'emotion' that is typically described as sentiment, a measure akin to the net emotion/utility measures envisaged by Bentham. These studies use sentiment as a measure that captures the myriad of emotions experienced by individuals. However, at any point in time, an individual can be subject to a range of emotions, some of which will have a positive impact on her/his state of mind (e.g., joy) while others will have a negative effect (e.g., stress). In this study, we provide greater insight into how emotions impact decision-making by conducting a more granular analysis of the impact of emotions on investors. We make use of a relatively new database, Thomson Reuters MarketPsych Indices, which provides an analysis of the words used in social and news media listings and calculates a minute-by-minute score for several different emotions relating to individual companies. We trace the impact of the emotions engendered in social and news media postings on the decision-making of investors by examining the relationship between emotions and stock price movements. The proposition is that the emotional tone of the postings can affect how market prices are impacted -- both directly and by way of the investor reaction to the unexpected component of earnings announcements. For example, suppose at a point in time, the postings in the media have an optimistic tone. This should translate into a higher market valuation and a more positive response to good news (positive unexpected earnings) and a less negative reaction to bad news (negative unexpected earnings).

Our findings support the proposition that the emotions expressed in both the news and social media impact on how investors value a company and how they react to information signals emanating from the company. We find that the aggregated measure across the individual emotions, *Aggregate_Emotion*, impacts on investor decisions as do the aggregate of each of the positive and negative emotions, and many of the individual emotions[16]. For example, we find that some of the positive emotions (e.g., joy and optimism) increase both the valuation that investors place on the company and the extent to which they react to news emanating from the company. Specifically, a positive emotion will increase the extent to which investors will respond to good news and decrease the extent to which they will react to bad news. These results reverse when it comes to negative emotions, some of which (e.g., stress and gloom) detract from company valuations and cause investors to respond less to good news and react more to bad news. However, we also establish that not all emotions are equal in terms of the influence they have on investor decision-making, with several of them (e.g., fear) having little or no impact on these decisions.

We find mixed results when we come to consider which of the media sources has a more significant influence on the investor. For some emotions (e.g., love/hate), we find that social media is more significant whereas, for other emotions (e.g., stress), it is the news media that exerts greater influence. Finally, we look at whether the influence of emotions on investors has changed over time by breaking up our 20 years of data into three sub-periods. Overall, we see that the influence of *Aggregate_Emotion* for positive news has increased over the three sub-periods, whereas for the first seven years of the sub-period, *Aggregate_Emotion* did not influence how investors reacted to bad earnings news.

[16] In total we have four positive emotions, five negative emotions, and one neutral emotion (surprise). The *Aggregate_Emotion* measure is the aggregate across the various emotions. We further calculate an aggregate positive score across the four positive emotions and an aggregate negative score across the five negative emotions.

4.2 Background

Research in psychology has long suggested that emotions are a principal driver for most important decisions, so it is unsurprising that we have seen an increasing interest in understanding the role emotions play in economic decisions (Lerner & Keltner, 2001; Smith & Lazarus, 1990). Keltner and Lerner (2010) describe the indelible link between emotions and decisions succinctly:

> Decisions serve as the conduit through which emotions guide everyday attempts at avoiding negative feelings (e.g., guilt, fear, regret) and increasing positive feelings (e.g., pride, happiness, love) [. . .] And once the outcomes of our decisions materialise, we often feel new emotions [. . .] emotion and decision-making go hand in hand. (p. 4)

Prior studies that have investigated how an investor's state of mind impacts their investment decisions have concentrated on emotions that are incidental to the decision being made. Incidental emotions generated by one event (e.g., bad weather or a favourite sports team losing) are carried over to influence the decisions of another event. For example, Schwarz and Clore (1983) find that people reported greater satisfaction with their life when the survey is conducted at a time when the sun is shining as compared to when the weather is overcast and rainy. Quigley and Tedeschi (1996) show that people tend to carry-over anger from one situation to project their anger onto a subject in an unrelated situation. Where financial decisions are concerned, the prevailing moods caused by an extraneous event appear to have the most relevance in determining returns. Saunders (1993) draws an association between the moods induced by weather and equity returns. The proposition is that cloudy days bring on negative moods, which will impact the trading behaviour of investors. He found that on days with heavy cloud cover, returns were significantly lower.

While incidental emotions can influence decision-makers, our interests in this study focus on integral emotions, directly connected to the decision, which is an area that is yet to receive much coverage in the literature. One example of integral emotions is where people who are concerned about global warming are more likely to avoid the purchase of fossil fuel-driven vehicles. Another instance relates to the decision itself, where it can generate emotions that again influence the decision being made. For example, it is not exceptional for individuals to feel anxious when making a difficult decision and it has been found that this anxiety will drive individuals towards making a safer choice rather than a potentially more lucrative but risky choice (Lerner et al., 2015). Some argue that such integral emotions drive individuals towards making better decisions (Pham, 2007)[17]. In this study, we examine the impact of such integral emotions. For example, we measure optimism relating to a firm on a day-by-day basis and trace how this optimism impacts on both the value that investors place on the firm and how they react to information disseminated by the firm.

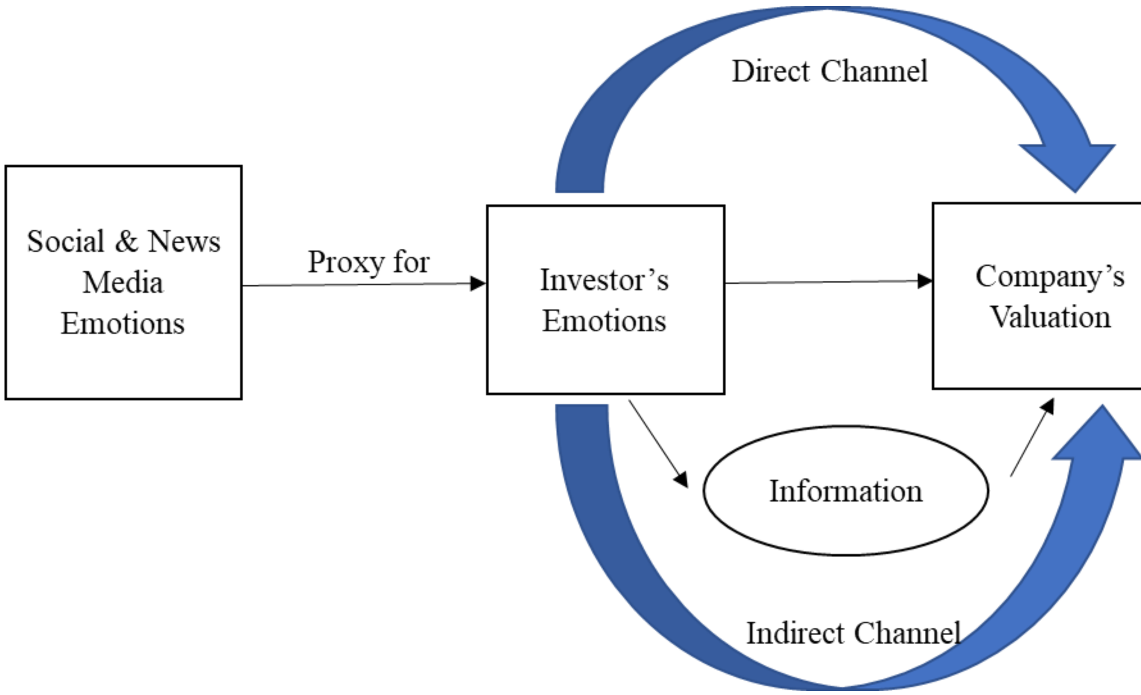
A common theme of the emotions literature is the employment of a valence approach where emotions are split into two 'camps': either good or bad or positive or negative emotions (Caplovitz Barrett, 2005). The idea is that individuals that are under the influence of positive emotions such as happiness and joy will view everything in a much more favourable light than individuals experiencing negative emotions (such as anger and fear). In this study, we draw upon this concept and divide the emotions into positive and negative emotions, and we

[17] Further proof of the benefits of integral emotion is found in neuroscience research (Bechara, Damasio, Tranel, & Damasio, 1997; Bechara, 2004; Damasio, 1994).

investigate how these emotions impact on investor reactions to both good and bad news. However, there are good reasons to believe that emotions of the same valence can induce different effects on decision-making. For example, both anger and fear are negative emotions, yet they have been found to induce a very different attitude to risks. An angry person is likely to have a greater appetite for risk-taking whereas fear may induce more pessimistic and risk-averse behaviour in decision-makers (Lerner & Keltner, 2001). Hence, we investigate whether the emotions of the same valence impart a similar effect on the financial decision-making of individuals. In so doing, to the best of our knowledge, we provide the most comprehensive study to date on how emotions impact investor valuations of companies.

The value of a firm is very much dependent on investor expectations of the firm's ability to generate future earnings and the perceived risks attached to these earnings. Our proposition, as represented in Figure 4.1, is that both emotions and new information will play a role in determining investor expectations and so the value of the company's stock. We test this by examining whether there is a direct link between emotions and company valuation and whether there is a less direct link wherein emotions condition the market's response to new information. Undoubtedly, one of the most relevant sources of information in forming these expectations is the announcement of corporate earnings. We examine how emotions impact on investors' reactions to the release of earnings by analysing the behaviour of a company's stock price around the time of the earnings release. Since we are aware of the possibility of a causality loop between returns and emotions, we include past returns in our analysis to control for the momentum in the stock returns. This will ensure that the effects we attribute to the emotions are not driven by the pre-announcement returns.

Figure 4.1: Proposed impact of emotions and new information on investors' expectations



Numerous studies in psychology (Dienstbier & Munter, 1971; Henrich et al., 2005) and marketing (H. Kim et al., 2010; Raghunathan et al., 2006), suggest that individual emotions have an impact on decision making. Although academics have tried to explain the impact of emotions on financial decision-making (Edmans et al., 2007; Hirshleifer & Shumway, 2003; Pevzner et al., 2015), a challenge for empirical research on emotions in finance is to find an appropriate measure of investor emotions (Griffith et al., 2019)[18]. Advances in computing and computational techniques in the past decade have resolved this problem.

In this thesis, we employ the 10 emotions indices generated by TRMI data derived from the textual analysis of both news and social media postings. We believe these indices represent an accurate indicator of investor emotions. The underlying logic to our model is that the social and

[18] For a detailed discussion, please refer to chapter 2.

news media proxy for investor emotions and second is that these emotions will impact the way investors respond to the information coming out of the company. In our case, that information is the earnings announcement. By applying the use of semantics to social and news media postings, researchers have been able to provide an accurate gauge of human emotion and how these emotions can impact financial markets[19]. It is very well recognized that emotions and feelings can be expressible in language, several studies have shown textual analysis to capture emotion in the text (Munezero et al., 2014). Further studies have confirmed the effectiveness and accuracy of these textual analysis techniques in capturing emotions (Liu Garcia et al. (2021), Mellert et al. (2021)). Mellert et al. (2021) compared emotion metric derived from social media postings with self-reported emotions from the UK's YouGov survey. The YouGov survey is a large self-response survey that includes questions on respondent's feelings (including happiness, anger and sadness), the survey elicits over 2000 responses each week. Mellert et al. (2021) used the emotion data from the YouGov survey to corroborate the accuracy of the textual analysis derived emotions remeasure. The authors found a high correlation between the textual analysis-based measures of emotions and self-reported feelings of the YouGov. Adding further merit to these textual analysis derived emotions measures, Garcia et al. (2021) showed when combined with user demographic data, emotions derived from advanced text analysis methods provide an accurate gauge of emotions in the general population.

One of the two channels that we examine is the direct impact an investor's state of mind has on a company's valuations. The literature on the impact of emotions on the financial market is thin.

[19] This aspect of emotions is discussed in more detail in Chapter 2.

The focus of existing literature has been on the effect of emotion's decedent, sentiment and its influence on stock prices. For example, De Long et al. (1990) showed that noise traders' sentiment causes the stock prices to diverge from their fundamental values. Barberis et al. (1998) Barberis et al. (1998) developed a model which showed that asset pricing is driven by investor sentiment. Tetlock et al. (2008) Tetlock et al. (2008) found that a sentiment measure derived from the media has an influence on market prices. Garcia (2013) Garcia (2013) utilised a similar method and found that the sentiment generated by the media is only effective during periods of crisis. One important distinction between these studies and this thesis is that the focus on emotions which promise to have a broader and more universal impact on stock prices[20]. Both Vamossy (2021) and Griifith et al (2019) have provided some evidence that emotions can influence stock returns.

Furthermore, a number of studies have also shown that information and sentiment from media sources can impact on prices. Blankespoor et al. (2014) demonstrated that companies reduce information uncertainty and increase liquidity in their stocks by employing Twitter to send investors links to press releases and other company-related news. However, it is not only Twitter postings emanating from companies that prove useful; as Bartov, Faurel, and Mohanram (2017) demonstrate, individually sourced twits themselves carry valuable information. Employing a 'wisdom of the crowd' measure, they found that the aggregate opinion of individuals collected from Twitter can predict a company's forthcoming earnings announcement. It should be noted that an often-cited concern with the use of social media information is the presumption that the posting represents the bona fide intent/emotions of the poster. However, Liu, Govindan, and Uzzi (2016) allayed much of these fears by showing that sentiment expressed in 1,234,822

[20] Please see earlier discussion on the differences between emotion and sentiment.

instant messages of 30 professional day traders are mostly consistent with their 886,000 trading decisions.

The second or indirect channel we examine is the extent to which emotions influence investor reaction to information released by companies. Numerous studies in the past 2 decades have theorised and used laboratory experiments to demonstrate that "emotion and decision-making go hand in hand." (Smith and Lazarus 1990; Isen, 2000; Loewenstein et al., 2001; Keltner & Lerner, 2001; Lucey and Dowling 2003; Keltner & Lerner, 2010). The way we feel influences our perceptions and conditions the manner that we respond to new information. For example, an angry person is likely to have a greater appetite for risk-taking (Gambetti & Giusberti 2012). In contrast, we expect fear to induce more pessimistic and risk-averse behaviour in the decision-makers (Lerner & Keltner, 2000; Lerner & Keltner, 2001). We test this second channel in this thesis and focus on earnings announcements as the information source, which has the advantage of being regularly announced by all firms, plus it has well-established implications for the stock market reaction. The fact that stock prices react to unexpected earnings announcements was first established by Ball and Brown (1968) who were also the first to provide evidence on what came to be known as the post-earnings announcements drift. Numerous studies have since confirmed that the stock price of companies underreacts at the time of an earnings announcement, and this is followed by a continuing a drift (i.e., abnormal returns in the same direction as the initial reaction). Several factors have been shown to affect the market reaction to earnings announcements including transaction cost (Bhushan, 1994); options (Roll et al., 2009); trading volume (Chae, 2005); market capitalisation (Poshakwale & Theobald, 2004); and liquidity (Chordia, Huh, & Subrahmanyam, 2009). Others have examined how market factors impact on investor reactions to information signals such as market sentiment (Baker & Wurgler, 2006;

Bird et al., 2014) and market uncertainty (Bird et al., 2014; Williams, 2015).The evidence quoted above supports our proposition that the emotions expressed in listings on both the news and social media will influence decision-making by investors. Below we have formulated a series of research questions to address in this study;

Question 1: Do the emotions expressed in the news and social media affect the decision-making of investors?

We break this down into two sub-questions:

Question 1a: Is there a direct relationship between each of the individual emotions, and their aggregate, emanating from the news and social media and the market valuation of a company?

Question 1b: Do each of the individual emotions, and their aggregate, emanating from the news and social media impact on how investors respond to new information (earnings announcements)?

To which we add two auxiliary questions:

Question 2: Which of the two sources of emotions (social media and news media) has a greater impact on investor decision-making?

Question 3: Has the influence of social media and news media changed over time?

The unique contribution of this study stems from its comprehensive nature in investigating the extent to which emotions impact on the behaviour of investors. This is largely owing to the comprehensiveness of the TRMI database that enables us to:

- Examine the impact of 10 measures of emotions whereas most studies are limited to examining only one measure which is typically an aggregate measure (typically called sentiment).
- Separately measure the emotions emanating from the news and social media.
- Utilise data on emotions that extends over thousands of companies collected on a minute-by-minute basis spanning over 20 years.

4.3 Data

This study utilises the quarterly time series data for companies listed on the S&P 500 from 1998 to 2017. We source emotions data from TRMI and use CRSP, Compustat, I/B/E/S, and CBOE for financial data. We use the firm size (Bernard & Thomas, 1989), earnings volatility and book-to-market (Hirshleifer et al., 2009), Friday (Hung et al., 2014), beta and loss (DeFond et al., 2007), FQ4 (Sun, 2015), VIX (Bird et al., 2014), and momentum (Boehmer & Wu, 2013; Ke & Ramalingegowda, 2005) as control variables[21].

4.4 Method

In our analysis, we study the behaviour of a company's stock at the time of the release of its earnings report. We define t = 0 as the day of the earnings announcement whereas t-1 and t+1 are the days before the announcement and the days after the announcement, respectively. If the announcement is made on a weekend or a public holiday, we move the announcement day to the next trading day, with t-1 and t+1 being adjusted accordingly. Consistent with standard practice, we use a two-day window to calculate the returns over the announcement period with

[21] Please refer to chapter 3 for data sources and data treatment techniques.

the period commencing at the close of trading on t=0 and ending at the completion of trading at t+1.

The basic model which we use to study the impact of an earnings announcement on stock returns is:

$$CAR_{i,t} = \alpha + \beta_1 UE_{i,t} + \beta_2 Ln(MV)_{i,t} + \beta_3 Log(BTM)_{i,t} + \beta_4 Beta_{i,t} + \beta_5 FQ4_{i,t} + \beta_6 Loss_{i,t} + \beta_7 VIX_{i,t} + \beta_8 Friday_{i,t} + \beta_9 Evol_{i,t} + \beta_{10} MoM_{i,t} + FQ\ Effects + Secotr\ Effects + \varepsilon_{i,t} \ldots \text{(Eq. 4.1)}$$

where $CAR_{i,t}$ is the cumulative abnormal return for a firm "i" over the event window "t" (in our case, t = 0, 1). $UE_{i,t}$ is the unexpected earnings for a firm "i" at time "t". The control variables have been described in chapter 3 and are included in Table 4.1. We have added the fiscal quarter effects (FQ effects) to account for the heterogeneity in price reactions over time. We have also added the sector effects to isolate within sector variations. For example, if a sector usually tends to have positive unexpected earnings, then adding sector effects will rule out that our results are driven by this. Literature suggests that the OLS standard errors can be biased and potentially can under(over)estimate the true variability of the coefficient estimates. To address this and make our model more robust, we follow Petersen (2009) and cluster the standard error by firms because there is a potential that the standard errors might be correlated over time at the firm level.

We next divide our sample into groups of good news and bad news. To find out the relationship between positive earnings surprise (PUE) and negative earnings surprise (NUE) with abnormal returns, we expand Equation 4.1 to incorporate the separation of PUE and NUE. The expanded equation is as follows.

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \sum\beta_k Control\ Variables + \sum Effects \quad + \varepsilon_{i,t} \ldots \text{(Eq 4.2)}$$

NUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there is a negative earnings surprise, and 0 otherwise. Similarly, PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there is a positive earnings surprise, and 0 otherwise. We would expect bad news to be associated with a fall in stock prices and good news to be associated with a rise in stock prices. Hence, we would expect a positive sign for both β_1 and β_2 – as NUE is negative, then a positive value for β_1 is consistent with a fall in prices after bad news.

We next introduce emotions into the analysis and test the direct relationships between emotions, abnormal returns, and the extent to which the reaction of investors is affected by the level of emotion before the announcement and change in emotion over the event window. To incorporate this, we expand Equation 4.2 as follows:

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t-1,1} + \sum\beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \quad \ldots$$

(Eq. 4.3)

X_1 is an indicator variable which is equal to 1 where firm "i" makes an earnings announcement at time t and the company's level of emotion at t-1 4pm is above median when all levels of emotions are ranked from low to high; otherwise $X_1 = 0$. X_2 is equal to 1 where there is an increase in the company's emotion level over the event window (as measured by the difference between the level of emotion at 4pm t+1and 4pm t-1); otherwise X_2 = 0.

We will define the level of an emotion as LOW when its value is below the median level before the event window (at t-1 4 pm), and it decreases over the event window. Similarly, we will define the level of the emotion as HIGH when the level of emotion is above the median level before the event window (at t-1 4 pm), and it increases over the event window. We run this regression equation for all our 10 individual and three aggregate emotion measures, and for each of our information sources (social and news combined, social only, and news only). If emotions have an impact on how investors respond to earnings announcements, we expect that there should be a difference in investors' reactions to earnings announcements when the news is released at the time when emotion is HIGH as compared to when the emotion is LOW. In the case of NUE, we would expect that high positive emotions would decrease the market reaction, whereas high negative emotions would increase the market reaction. We can test these expectations by observing the sign and significance of β_3 + β_5 in Equation 4.3. In the case of PUE, we expect that high positive emotions would increase the market response whereas high negative emotions would decrease the market response. We can test these expectations by observing the sign and significance of β_4 + β_6 in Equation 4.3. The other two variables of interest are $FEt_{i,t-1}$ and $\Delta FEt_{i,t-1,1}$which represent the absolute level of a company's emotion at 4pm t-1 and the change in the company score of the emotion between 4pm t-1 and 4pm t+1, respectively. If either β_7 and/or β_8 are significant, then it is indicative that the level of and/or the direction of emotions have a direct impact on the abnormal returns.

A summary of the variables included in our analysis is set out in Table 4.1 and summary statistics are presented in Tables 4.2 and 4.3. We see that PUE represent about 75% of the sample but the magnitude of NUE is about twice that of PUE. However, we also see that the standard deviation of NUE is much higher than the standard deviation of PUE. The evidence suggests that there is not much difference between the level of emotion emanating from social media to the level emanating from the news media. There is certainly more joy and love/hate generated by social media although this is somewhat balanced by the fact that gloom and anger are also slightly higher for social media. Overall, this suggests that social media is more likely to witness more extreme expressions of emotions.

Table 4.1: Summary of Variables to be Included

Variable	Description	Expected Sign	Range
UE	Difference between the actual EPS and the median value of the latest consensus earnings estimated by analysts. Scaled by the absolute value of actual EPS.	+	
Ln (MV)	Market capitalization at the end of quarter t-1.	-	
BTM	The logarithm of book-to-market (BTM) ratio	+	
VIX	The closing value of Implied Volatility Index at t-1	+	
Beta	Estimate on market returns in a market model regression for firms with daily returns in the 250 trading days before the earnings announcement. Observations which had less than 100 trading days for estimation were dropped.	+	
FQ4	A dummy variable which takes the value of 1 if the announcement is in the fourth-fiscal quarter, otherwise its value is 0.	+	
Loss	A dummy variable which takes the value of 1 if I/B/E/S value of actual EPS is negative, otherwise its value is 0.	-	
Friday	A dummy variable which takes the value of 1 if the announcement was made on Friday, otherwise its value is 0.	-	

Evol	Earnings volatility, calculated as the standard deviation during the preceding four years of the deviations of quarterly earnings from one-year-ago earnings (minimum 4 observations required).	-	
Momentum	Company’s abnormal return immediately before the earnings announcement (i.e., from T-1 to T-6).	-	
PUE	Positive Unexpected Earning	+	
NUE	Negative Unexpected Earning	+	
	Aggregate_Emotion		
Agg. Emotion	Overall emotion score including 4 positive and 5 negative emotions		-1 to +1
	Positive Emotions		
Optimism	Optimism, net of references to pessimism		-1 to +1
Joy	Happiness and affection		0 to 1
Trust	Trustworthiness, net of references connoting corruption		-1 to +1
Love/Hate	Love, net of references of hate		-1 to +1

Agg. Positive	Average score of all four positive emotions	-1 to +1
	Negative Emotions	
Stress	Distress and danger	0 to 1
Gloom	Gloom and negative future outlook	0 to 1
Fear	Fear and anxiety	0 to 1
Anger	Anger and disgust	0 to 1
Conflict	Disagreement and swearing net of agreement and conciliation	-1 to +1
Agg. Negative	Average score of all five negative emotions	-1 to +1
	Neutral Emotion	
Surprise	Unexpected events and surprise	0 to 1

Table 4.2: Summary Statistics

	N	Mean	SD
CAR (0, 1)	45191	0.0030	0.0591
UE	45191	0.0268	0.4048
NUE	11504	-0.3223	0.5260
PUE	33687	0.1460	0.2637
Ln (MV)	45191	9.0360	1.2939
BTM	45191	0.5045	0.0711
Beta	45191	1.1599	0.5912
Vix	45191	19.7280	8.3629
FQ4	45191	0.2388	0.4264
Loss	45191	0.0674	0.2508
Friday	45191	0.0669	0.2498
Evol	45191	0.2910	0.3313
Momentum	45191	0.0008	0.0484

Table 4.3: Summary Statistics of Emotions

	Social			News			News & Social		
Emotion	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**
Agg. Emotion	18028	-0.0153	0.0814	15909	-0.0152	0.0768	25300	-0.0136	0.0734
∆Agg. Emotion	18028	0.0030	0.0802	15909	0.0042	0.0732	25300	0.0036	0.0689
Optimism	23851	0.0286	0.2102	22407	0.0325	0.1858	31245	0.0273	0.1747
∆ Optimism	23851	-0.0125	0.2321	22407	-0.0252	0.2013	31245	-0.0181	0.1909
Joy	13700	0.0379	0.0629	7777	0.0233	0.0453	17130	0.0273	0.0493
∆ Joy	13700	-0.0157	0.0631	7777	-0.0137	0.0449	17130	-0.0152	0.0497
Trust	17649	0.0055	0.0350	16222	0.0052	0.0322	24678	0.0050	0.0286
∆ Trust	17649	-0.0010	0.0356	16222	0.0020	0.0338	24678	0.0010	0.0308
Love/Hate	12360	0.0218	0.0587	7670	0.0178	0.0393	16074	0.0174	0.0450
∆ Love/Hate	12360	-0.0101	0.0559	7670	-0.0106	0.0371	16074	-0.0104	0.0436
Stress	21563	0.0752	0.0912	22326	0.0855	0.0940	30004	0.0736	0.0833
∆ Stress	21563	-0.0223	0.0970	22326	-0.0446	0.0978	30004	-0.0325	0.0880
Gloom	17971	0.0497	0.0705	15364	0.0391	0.0627	24299	0.0404	0.0605
∆ Gloom	17971	-0.0143	0.0749	15364	-0.0170	0.0645	24299	-0.0161	0.0636
Fear	10616	0.0199	0.0441	8863	0.0184	0.0375	15344	0.0160	0.0331
∆ Fear	10616	-0.0093	0.0405	8863	-0.0101	0.0374	15344	-0.0085	0.0327
Anger	11937	0.0279	0.0500	6037	0.0167	0.0342	14633	0.0202	0.0390
∆ Anger	11937	-0.0110	0.0484	6037	-0.0101	0.0311	14633	-0.0112	0.0377
Conflict	23140	-0.0057	0.1521	22005	0.0079	0.1215	30615	0.0019	0.1215
∆ Conflict	23140	0.0038	0.1593	22005	-0.0034	0.1253	30615	0.0013	0.1264
Surprise	11957	0.0361	0.0999	10571	0.0454	0.1033	17651	0.0351	0.0890
∆ Surprise	11957	-0.0174	0.0941	10571	-0.0295	0.0990	17651	-0.0215	0.0862
Agg. Positive	19596	0.0244	0.0765	17104	0.0213	0.0682	26650	0.0206	0.0644
∆ Agg. Positive	19596	-0.0108	0.0743	17104	-0.0137	0.0660	26650	-0.0120	0.0609
Agg. Negative	21782	0.0392	0.0626	21542	0.0409	0.0580	29913	0.0357	0.0546
∆Agg.Negative	21782	-0.0133	0.0586	21542	-0.0208	0.0500	29913	-0.0166	0.0480

4.5 Findings

In this section, we report on our findings as to how that the state of emotions emanating from the news and social media impacts on the valuation of companies, both through the direct channel and how the market reacts to information flowing from the company.

4.5.1 Market Reaction

As the first step towards investigating whether emotions have an impact on the way investors respond to new information, we first need to establish that the new information affects a company's share price. To analyse this, we applied Equation 4.1 to our data, and our findings are reported in Table 4.4. The coefficient reported for unexpected earnings (β_1=0.0239***) clearly shows that there is a significant reaction to the earnings announcement (i.e., good news has a positive impact on the value of a company, and bad news has a negative impact)[22]. The sign of the coefficient attached to each of the control variables is generally as expected. For example, we detect a size and value effect in the announcement period of abnormal returns. There is also a noticeable Friday effect where abnormal returns are lower where the announcement occurs on a Friday. Interestingly, the coefficient associated with our momentum measure suggests a reversal in the announcement period. This reversal in returns is consistent with the findings in Vamossy (2020), who documents a similar turnaround in returns in the announcement period.

[22] It has to be recognised that the values for NUE are negative and so a positive coefficient informs us that NUE has a negative impact on the value of a company.

Table 4.4: Regression Results of Unexpected Earnings

	CAR (0, 1)
UE	0.0239***
Ln (MV)	-0.0023***
BTM	0.0188***
Beta	0.0015**
VIX	0.0007*
FQ4	-0.0010
Loss	-0.0118***
Friday	-0.0026***
Evol	-0.0003
Momentum	-0.0712***
Obs.	45191
Effects	Yes
SE clustering	Yes

The equation which we are going to use in our analysis is

$$CAR_{i,t} = \alpha + \beta_1 UE_{i,t} + +\sum\beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ldots \text{(Eq 4.1)}$$

where $CAR_{i,t}$ is the cumulative abnormal return for firm "i" over the event window "t" (in our case, t = 0, 1). $UE_{i,t}$ is the unexpected earnings for firm "i" at time "t". The control variables utilised have previously been defined in chapter 3 and are set out in Table 4.1. We also add different effects and cluster standard errors. **** p<0.01, ** p<0.05, * p<0.1.*

Several studies have shown that the magnitude of the investor response can differ between good news and bad news (Bird & Yeung, 2012; Williams, 2015). Therefore, we apply Equation 4.2 to our data to separate our unexpected earnings into bad news (NUE) and good news (PUE). The coefficients reported in Table 4.5 for NUE (β_1=0.0168***) and PUE (β_2=0.0339***) confirm that investors react to both negative and positive news, with the response being greater for a quantum of good news than it is for a quantum of bad news. This finding differs from some previous findings and perhaps reflects that we are using a smaller database (S&P500) than that used in many of these studies.

Table 4.5: Regression Results of Negative and Positive Unexpected Earnings

	CAR (0, 1)
NUE	0.0168***
PUE	0.0339***
Ln (MV)	-0.0019***
BTM	0.01781***
Beta	0.0009
VIX	0.0007
FQ4	0.0009
Loss	-0.0144***
Friday	-0.0027***
Evol	-0.0012
Momentum	-0.0707***
Number of observations	45191
Effects	Yes
SE Clustering	Yes

The above table reported the results for regression Eq. 4.2

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \text{ ... (Eq. 4.2)}$$

where $CAR_{i,t}$ is the cumulative abnormal return for firm "i" over the event window "t" (in our case, t = 0, 1). The unexpected portion of the earnings announcement is defined as the difference between the actual EPS and the latest median consensus analysts' forecast, scaled by the absolute value of actual EPS. We further divide the Unexpected Earnings into Positive Unexpected Earnings (PUE) and Negative Unexpected Earnings (NUE). PUE are events where the announced earnings are greater than or equal to the latest median consensus analyst forecast earnings. PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of

1 if there are positive earnings surprises and 0 otherwise. Similarly, the NUE event occurs when the earnings just announced fall short of the latest median consensus analyst forecast earnings. NUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are negative earnings surprises and 0 otherwise. The control variables utilised have previously been defined in chapter 3 and are set out in Table 4.1. We also add different effects and cluster standard errors. *** *p<0.01*, ** *p<0.05*, * *p<0.1*.

4.5.2 Market Reaction to Emotions

While many studies have attempted to use firm-level characteristics to explain the investor reaction at the time of earnings announcements, little has been done to investigate the impact of emotions on the relationship between earnings announcements and stock price adjustment (Griffith et al., 2019). In this study, we investigate the extent to which a wide range of emotions generated by the news and social media play a role in determining asset values either directly or by way of the market response to the release of new information. By so doing, we have a vehicle for determining the extent to which the emotions expressed in listings in the news and social media impact on the decision-making of investors. To undertake this analysis, we estimate Equation 4.3 using data on our 10 individual emotions measured at the company level and derived from the social media, the news media, and the two media sources combined. As indicated in Table 4.1, we have divided the various emotions into four positive emotions, five negative emotions, and one neutral emotion (surprise). We have also calculated aggregate positive emotions, which is the aggregation of the four positive emotions, and aggregate negative emotions, which is the composite of the five negative emotions. Finally, we added the aggregate positive emotion score and the aggregate negative emotions score to obtain the grand composite score, *Aggregate_Emotions*.

We conduct our analysis following a top-down approach commencing with an investigation as to how does *Aggregate_Emotion*, the composite of the positive and negative emotions, impact on market valuations. We next examine the positive component and the negative component of the *Aggregate_Emotion* score separately. As a final step, we then examine how each of the 10 individual emotions impact on company valuations. By tackling the analysis in this way, we can explore in depth the emotional drivers of investor behaviour and undertake a more thorough analysis of the role that emotions play in influencing investor decision-making, and ultimately, asset prices.

4.5.2.1 Aggregate_Emotion

The sole emotion investigated in most studies to date has been sentiment which typically reflects some composition of individual emotions frequently hand-collected from very limited media sources. Our equivalent is *Aggregate_Emotion* which is a composite of nine different emotions drawn from the TRMI database. *Aggregate_Emotion* has advantages in terms of the frequency of calculation, the length of the data series, and the breadth of the media sources that are analysed (Peterson, 2016). From our findings reported in Table 4.6, we observe that both the level (FEt-1) of, and change (ΔFEt-1 to 1) in, the *Aggregate_Emotion* score have a *direct* impact on returns. We see a higher *Aggregate_Emotion* score and an increase in the score, both translating to higher share prices. The results confirm that market valuations are influenced by emotions generated by postings in both the news and social media. However, of the two, it is the *Aggregate_Emotion* emanating from the news media that has, by far, the greater direct impact on market valuations.

We previously observed that a negative earnings surprise typically harms stock prices (NUE = 0.0168*** from Table 4.5). We expect that when *Aggregate_Emotion* is high (which we define as high, and increasing, *Aggregate_Emotion*), this will cause investors to take a more positive stance when interpreting bad news and so result in a smaller adverse market reaction to this news. Consistent with these expectations, we see that when *Aggregate_Emotion*, as calculated from the news and social media combined, is at a high level at the time of the release of negative earnings news, the magnitude of the adverse reaction is much lower than average (NUE = 0.0121** < 0.0168***). However, when a negative earnings surprise occurs at a time when *Aggregate_Emotion* is low, the market response is more significant than is typically the case (NUE = 0.0209*** > 0.0168***). Overall, we see that a negative earnings surprise causes investors to adjust down a company's stock price. However, we see that this downward adjustment is lower if the negative earnings are released at a time when *Aggregate_Emotions* are high as compared to when they are low, but we note that the extent of the difference is not significant.

We see from Table 4.5 that the coefficient for PUE across the whole sample is 0.0339***, which confirms that on average, there is a positive reaction to a positive earnings surprise. When we look at the coefficient for PUE associated with earnings releases made at a time when sentiment is high, we see a market reaction that is much greater than what we reported earlier (PUE = 0.05821*** > 0.0339***). Again, this finding is very much consistent with our expectation that good news released by a company will have a more positive impact on market prices if it becomes available at a time when the media is expressing very positive *Aggregate_Emotion*. However, if we look at the market reaction to good earnings news released at a time when *Aggregate_Emotion* is low, we see that the market reaction is much lower than what it is in more typical times (PUE = 0.00839 < 0.0339***). Indeed, we find that good earnings news released at a time when *Aggregate_Emotion* is low is effectively ignored by investors as the earnings news has no significant impact on stock prices. Further, the difference in the impact of the positive announcements over the announcement period between when *Aggregate_Emotion* is high and when it is low (0.0498***) is highly significant, which demonstrates the extent of the impact that *Aggregate_Emotion* has on investor reaction to good earnings news.

Consistent with Karampatsas et al. (2018), our results clearly show that sentiment measures based on an analysis of both the news and social media impact on investor reaction to earnings announcements, and particularly, positive earnings announcements. However, they diverge from the findings of Guo, Sun, & Qian (2017) who, when using textual analysis of internet sources to generate a sentiment index, concluded that sentiment data did not influence investor reaction to earnings announcements.

To summarise, we find strong evidence to suggest that both the level of, and movements in the level of, *Aggregate_Emotion* has a direct impact on stock prices, with the emotions emanating from news media having the greater impact. With respect to the indirect path, we also find evidence to suggest that *Aggregate_Emotion* impacts on how investors respond to earnings news, and particularly good earnings news. In this case, it is still the emotions emanating from the news media that has the greater impact but to a lesser extent than was the case for the direct path.

Table 4.6: Impact of *Aggregate_Emotion* on Response to Earnings Announcements

			Social + News	Social Media	News Media
Agg.Emotion	NUE	Hi Agg.Emotion	0.01211**	0.02245***	0.01183**
		Lo Agg.Emotion	0.02088***	0.01264**	0.02726***
		Difference	-0.00877	0.00981	-0.01543
	PUE	Hi Agg.Emotion	0.05821***	0.0506***	0.05515***
		Lo Agg.Emotion	0.00839	0.01615***	0.01142*
		Difference	0.04982***	0.03445***	0.04373***
	Company	FEt-1	0.11357***	0.04608***	0.12341***
		ΔFEt-1 to 1	0.16644***	0.08520***	0.17646***

The above table reports the results for the following regression.

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t-1,1} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ldots \text{(Eq. 4.3)}$$

The dependent variable $CAR_{i,t}$ is the cumulative abnormal return over the event window. The unexpected portion of the earnings announcement is defined as the difference between the actual EPS and the latest median consensus analysts' forecast, scaled by the absolute value of actual EPS. PUE are events where the announced earnings are greater than or equal to the consensus analyst forecast earnings. PUE are also events where the announced earnings are greater than the expected median analysts' forecast earnings. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of the expected median analysts' forecast earnings. NUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are negative earnings surprises and 0 otherwise. X1 is an indicator variable which is equal to 1 where firm "i" makes an earnings announcement at time t and the level of emotion at time t-1 4pm is above median when all levels of emotion are ranked from low to high; otherwise X1 = 0. X2 is equal to 1 where there is an increase in the level of emotion over the event window (as measured by the difference between the level of emotion at 4pm t+1and 4pm t-1); otherwise X2 = 0. Finally, $FEt_{i,t-1}$ is the emotion score for a firm "i" at 4pm t-1 and $\Delta FEt_{i,t-1,1}$ is the change in the emotion score of a firm "i" between 4pm t-1 and 4pm t+1 (the actual value and not the dummy variable). The control variables utilised have previously been defined in the paper and are set out in Table 4.1. We perform a Wald-test to determine if the coefficients are statistically significant from zero. We also use different effects and following the literature, we have clustered standard errors to make our regressions more robust. *** p<0.01, ** p<0.05, * p<0.1

4.5.2.2 Aggregate Positive Emotion and Aggregate Negative Emotion

We have established that *Aggregate_Emotion* has a significant influence on investor behaviour. However, *Aggregate_Emotion* is an aggregation across a whole spectrum of emotions, some of which will contribute to an investor's state of mind in a positive sense, and others in a negative sense. In the pursuit of gaining a greater understanding of the impact of emotions, we break emotions down into a positive and negative component (i.e., valence) in order to better understand the contribution that each makes to our finding for *Aggregate_Emotion*.

<u>Aggregate Positive and Negative Emotions</u>

Our findings for aggregate positive emotions and aggregate negative emotions are reported in Table 4.7. We start by considering the direct impact that aggregate positive and negative emotions have on market valuations. Based on the combined emotions emanating from the news and social media, we find that both aggregate positive and negative emotions have the expected significant impact with positive emotions being associated with an increase in market valuations and negative emotions being associated with a decrease. Further, it is the aggregate positive emotions that has the greater absolute impact, which is consistent with our previous finding that *Aggregate_Emotion* has a positive impact on market valuations. Also consistent with our findings for *Aggregate_Emotion*, we find that the news media has, by far, the greater influence on investors when judged on the basis of its influence through the direct channel.

We find that aggregated emotions, when measured across the news and social media combined, have the expected impact on how investors react to the release of earnings news. Positive emotions significantly decrease the impact of bad news and increase the impact of good news. In contrast, negative emotions significantly increase the impact of bad news and reduce the impact of good news. Our findings would suggest that not only does the sum of all the emotions (*Aggregate_Emotion*) impact on how investors react to information, but the aggregate of the positive and negative components, when measured across both the news and social media, does likewise.

We do start to see some departures from our findings when we examine the influence of the aggregated positive and negative emotions generated by either social media or the news media. As with *Aggregate_Emotions*, we see that in the case of negative earnings surprise, the impact of negative emotions is in the predicted direction but again the impact proves to be insignificant. For positive emotions and negative earnings surprise, we see that the negative news is ignored when it is released at the time when positive emotions are high and the market reaction is amplified when it is released at a time when positive emotions are low. Furthermore, with positive earnings surprise, the influence of both aggregate positive and negative emotions is in the expected direction but in this case highly significant. Again, it is the emotions generated from the news media that has by far the greater impact on investor behaviour which confirms our previous finding that the news media has a greater influence on investor behaviour than social media.

Table 4.7: Aggregate Positive Emotions (optimism, joy, trust, and love/hate) and Aggregate Negative Emotions (stress, gloom, fear, anger, and conflict)

			Social + News	Social Media	News Media
Agg_positive	**NUE**	**Hi Agg_positive**	0.00648	0.01337***	0.0134***
		Lo Agg_positive	0.02378***	0.02050***	0.02529***
		Difference	-0.0173**	-0.00713	-0.01189
	PUE	**Hi Agg_positive**	0.06062***	0.0529***	0.04705***
		Lo Agg_positive	0.01599***	0.02017***	0.02613***
		Difference	0.04463***	0.03273***	0.02092*
	Company	**FEt-1**	0.12205***	0.05030***	0.13892***
		ΔFEt-1 to 1	0.16465***	0.07270***	0.19181***
Agg_negative			**Social + News**	**Social Media**	**News Media**
	NUE	**Hi Agg_negative**	0.02372***	0.01858***	0.02063***
		Lo Agg_negative	0.01363***	0.01689***	0.01533***
		Difference	0.01009	0.00169	0.0053
	PUE	**Hi Agg_negative**	0.02155***	0.02334***	0.01814***
		Lo Agg_negative	0.04152***	0.04224***	0.04011***
		Difference	-0.01997***	-0.0189**	-0.02197**
	Company	**FEt-1**	-0.05413***	-0.01463*	-0.05715***
		ΔFEt-1 to 1	-0.09826***	-0.04451***	-0.08424***

See annotations to Table 4.6

4.5.2.3 Individual Emotions

We would argue that the composite of all of our emotions contributes to an investor's state of mind which is captured by our *Aggregate_Emotion* score. In our initial analysis, we found evidence to suggest that *Aggregate_Emotion* impacts on stock valuations through what we describe as the direct and the indirect channels. When we split *Aggregate_Emotion* into its positive and negative components, we found again that both made their expected contribution to the linkage between emotions and stock valuations. We will now further decompose the aggregated scores into the 10 individual emotions to further explore the specifics of how emotions influence investor decisions, and in particular, to identify which of the emotions are the greatest drivers of investor behaviour. We will examine the four positive emotions (optimism, joy, trust, love/hate), the five negative emotions (stress, gloom, fear, anger, and conflict), and the one neutral emotion (surprise).

<u>Individual Positive Emotions</u>

We discuss in this section the four positive emotions that contribute both to our measure of aggregate positive emotions and to *Aggregate_Emotion*. We are interested in the extent to which each of the individual emotions contribute to the behaviour of investors that we have already identified at the aggregate level. Our findings are summarised in Table 4.8 for each of the four positive emotions: optimism, joy, trust, and love/hate. Again, we will first examine the direct channel as reflected by the coefficients attached to $FEt_{i,t-1}$ and $\Delta FEt_{i,t-1,1}$. We see that each of the four emotions, when measured across the combination of the news and social media, have the expected positive impact on returns. The extent to which emotions influence security prices are very strong in the case of trust, optimism, and joy but it is weaker in the case of love/hate, largely because the love/hate emotion emanating from the news media would seem to have no influence on stock valuations. We found previously, when evaluating the aggregate positive emotions, that it was the emotions emanating from the news media that had the greater direct impact on investor behaviour. We find mixed results on this score when we examined the direct influence of each of the individual positive emotions. The news media has the stronger influence in the case of optimism and trust while social media has the greater influence in the case of joy and love/hate. Overall, the news media outstrips social media by a greater degree when it comes to optimism and trust than social media does in the case of joy and love/hate. We, therefore, end up with the previously reported finding that, overall, the news media is more influential when it comes to positive emotions.

We find strong support for the existence of the second channel through which emotions generated by the media influence the extent to which investors react to unexpected earnings news. However, there is variation in the strength of this relationship across the four individual positive emotions. In the case of a positive earnings surprise, each of the four emotions generated by a combination of the news and social media have the expected impact of boosting the response to good news. This influence is strongest in the case of both optimism and trust and not statistically significant in the case of both joy and love/hate. Similarly, with negative earnings surprise, we find the expected result that each of the four positive emotions dampen the investor response to bad earnings news. In this case, the finding is strongest for optimism, joy, and love/hate and not statistically significant for trust. All four individual positive emotions would seem to play an important role in influencing investor behaviour, with optimism appearing to be the most important contributor of the four. In terms of whether social media or the news media contributes more to the influence of each of the positive emotions, it is clear that for love/hate, social media is the greater contributor. However, it is difficult to identify which is the major contributor in terms of the three other positive emotions.

Table 4.8: Impact of Positive Emotions on the Response to Earnings Announcements

			Social + News	Social Media	News Media
Optimism	**NUE**	**Hi optimism**	0.00768*	0.01237***	0.01993***
		Lo optimism	0.02148***	0.02070***	0.01245***
		Difference	-0.0138**	-0.00833	0.00748
	PUE	**Hi optimism**	0.05113***	0.05453***	0.04844***
		Lo optimism	0.01802***	0.01629***	0.01916***
		Difference	0.03311***	0.03824***	0.02928***
	Company	**FEt-1**	0.09497***	0.03047***	0.10357***
		ΔFEt-1 to 1	0.09630***	0.03292***	0.10716***
Joy			**Social + News**	**Social Media**	**News Media**
	NUE	**Hi joy**	0.00333	0.00657	-0.00255
		Lo joy	0.02803***	0.02757***	0.03390***
		Difference	-0.0247***	-0.021**	-0.03645***
	PUE	**Hi joy**	0.04659***	0.05478***	0.06002***
		Lo joy	0.03225***	0.02509***	0.02250***
		Difference	0.01434	0.02969***	0.03752**
	Company	**FEt-1**	0.10195***	0.06160***	0.05052
		ΔFEt-1 to 1	0.09670***	0.06708***	0.04779
Trust			**Social + News**	**Social Media**	**News Media**
	NUE	**Hi trust**	0.01363**	0.0195***	0.01353**
		Lo trust	0.02095***	0.01747***	0.02748***
		Difference	-0.00732	0.00203	-0.01395

	PUE	Hi trust	0.05137***	0.04606***	0.04191***
		Lo trust	0.02327***	0.02846***	0.03104***
		Difference	0.0281***	0.0176*	0.01087
	Company	FEt-1	0.31183***	0.14165***	0.31887***
		ΔFEt-1 to 1	0.33058***	0.15535***	0.34697***
Love/Hate			**Social + News**	**Social Media**	**News Media**
	NUE	Hi love/hate	0.00449	0.01118*	0.01881**
		Lo love/hate	0.02498***	0.02207***	0.02006***
		Difference	-0.02049**	-0.01089	-0.00125
	PUE	Hi love/hate	0.04761***	0.06253***	0.04671***
		Lo love/hate	0.03058***	0.01889***	0.03469***
		Difference	0.01703	0.04364***	0.01202
	Company	FEt-1	0.04466**	0.02736*	0.00238
		ΔFEt-1 to 1	0.04515**	0.04505***	-0.01794

See annotation to Table 4.6

Individual Negative Emotions

In this section, we evaluate the impact of five negative emotions generated by the social and/or news media on stock prices, either directly or by way of their influence on investor response to earnings announcements. The negative emotions are stress, gloom, fear, anger, and conflict. We propose that a high value for these negative emotions will lead to lower stock prices and a reduced (increased) price reaction to unexpected positive (negative) earnings. Our findings concerning the impact of each of the five negative emotions on stock prices are summarised in Table 4.9.

The highest-level observation that we would make is that, in contrast to our findings for the four positive emotions, not all of the five individual negative emotions make a contribution to the findings that we have previously observed at the aggregate level. For example, we have found that aggregate negative emotion has a direct negative impact on stock valuations. However, when we examine this at the level of individual negative emotions, we find that only stress, gloom, and conflict make such a contribution with stock valuations being seemingly unaffected by either fear or anger. We also find that both social and news media make an important contribution to our finding for that stress, gloom, and conflict each have a direct impact on stock valuations, but in the case of stress and gloom, it is news media that has the greater influence.

We next turn to our findings on how negative emotions influence investor response to unexpected earnings. We find that stress, gloom, and conflict each play an important role in shaping investor response to positive earnings news in that higher levels for each of these three negative emotions dampen the impact that bad earnings news has on stock valuation. When it comes to negative earnings news, it is only stress and gloom that impact on investor behaviour by causing them to react more to the bad news which, in turn, causes a greater fall in stock valuations. Again, we find that neither fear nor anger play a role in conditioning an investor’s response to the release of unexpected earnings. When it comes to determining which of the two media sources has greater influence over investors when it comes to responding to negative emotions, we find that in the case of stress, it is the news media that has the greater influence, in the case of conflict, the social media has the greater influence, while in the case gloom the two media sources have a similar influence.

Although we provide strong evidence that the aggregate of the nine individual emotions (i.e., *Aggregate_Emotion*) impacts on the decision-making of investors and so corporate valuations, when we examine the five individual negative emotions, it is clear that not all of them contribute to this outcome. Indeed, it is clear that only stress, gloom, and conflict have an influence across the direct and indirect channels. Importantly, we find that neither anger nor fear has any discernible influence on how the decisions made by investors. Of these two emotions, the findings for fear are perhaps the more surprising as statements are often made as to how stock prices are moved by ‘greed’ and ‘fear’ (Breaban & Noussair, 2018). We surmise that the supposed impact of fear is captured by stress, and even gloom, which results in fear not showing a significant influence on investor decision- making.

Table 4.9: Impact of Stress on Response to Earnings Announcements

			Social + News	Social Media	News Media
Stress	NUE	Hi stress	0.02767***	0.02338***	0.02746***
		Lo stress	0.01034***	0.01399***	0.01231***
		Difference	0.01733**	0.00939	0.01515*
	PUE	Hi stress	0.01745***	0.0254***	0.02037***
		Lo stress	0.04273***	0.04046***	0.03783***
		Difference	-0.02528***	-0.01506*	-0.01746**
	Company	FEt-1	-0.14351***	-0.04279***	-0.12127***
		ΔFEt-1 to 1	-0.15229***	-0.05300***	-0.12690***
Gloom			Social + News	Social Media	News Media
	NUE	Hi gloom	0.02348***	0.02521***	0.02416***
		Lo gloom	0.00898**	0.00949**	0.01051*
		Difference	0.0145**	0.01572*	0.01365
	PUE	Hi gloom	0.01618***	0.02793***	0.02167***
		Lo gloom	0.04768***	0.03950***	0.04058***
		Difference	-0.0315***	-0.01157	-0.01891
	Company	FEt-1	-0.23034***	-0.06081***	-0.24951***
		ΔFEt-1 to 1	-0.24726***	-0.07271***	-0.26726***
Fear			Social + News	Social Media	News Media
	NUE	Hi fear	0.02612***	0.02445***	0.01707**
		Lo fear	0.01075**	0.00827	0.02493***
		Difference	0.01537*	0.01618	-0.00786
	PUE	Hi fear	0.02821***	0.03225***	0.02762***
		Lo fear	0.04118***	0.03992***	0.04115***

		Difference	-0.01297	-0.00767	-0.01353
	Company	FEt-1	-0.02164	0.01397	-0.03103
		ΔFEt-1 to 1	-0.01920	0.03682*	-0.04175
Anger			**Social + News**	**Social Media**	**News Media**
	NUE	Hi anger	0.02816***	0.03057***	0.02391***
		Lo anger	0.01331***	0.01195**	0.02381***
		Difference	0.01485	0.01862*	0.0001
	PUE	Hi anger	0.02608***	0.02878***	0.03538***
		Lo anger	0.04075***	0.03769***	0.04475***
		Difference	-0.01467	-0.00891	-0.00937
	Company	FEt-1	0.03722	0.02178	0.09000*
		ΔFEt-1 to 1	0.02725	0.03288*	0.09526
Conflict			**Social + News**	**Social Media**	**News Media**
	NUE	Hi conflict	0.01844***	0.0168***	0.01781***
		Lo conflict	0.01596***	0.01746***	0.01927***
		Difference	0.00248	-0.00066	-0.00146
	PUE	Hi conflict	0.02346***	0.02718***	0.0302***
		Lo conflict	0.04621***	0.04610***	0.03610***
		Difference	-0.02275**	-0.01892**	-0.0059
	Company	FEt-1	-0.02450***	-0.01316***	-0.01838**
		ΔFEt-1 to 1	-0.02864***	-0.01710***	-0.01516**

See annotation to Table 4.6

Neutral Emotion

All of the nine emotions previously considered could be classified as being either positive or negative in terms of their likely impact on an investor's state of mind and so one can articulate their expected impact are likely to have on how investors would value stocks and respond to information signals. Surprise, which is defined by TRMI as "unexpected events and surprise" differs from the other nine emotions in that is does not differentiate between a good and a bad surprise. As such, it is not possible to predict the direction of the impact that surprise will have on the market's response to an earnings announcement. Our interpretation is further complicated by the fact that we are actually dealing with two surprises: that emanating from the media listings and also that associated with the earnings announcement. In Table 4.10, we report our findings on the influence that surprise has on investor decision-making.

The evidence suggests that surprise has a very limited direct impact on stock prices, with the only instance being that the surprise expressed in the news media has a small negative impact on stock prices. When it comes to the market reaction to the release of good earnings news, we see that there is a greater investor response to the news at times when surprise is at a high level. Closer investigation suggests that this result is solely driven by surprise emanating from social media. When we investigate the influence that surprise has on investor reaction to the release of poor earnings news, we find that based on the combined surprise score, investors would appear to be unaffected by the level of surprise. However, this finding hides the fact that the actual impact of surprise concerning the reaction to disappointing earnings news is dependent on the media type in which the emotion is sourced. If the surprise is generated by social media, then it behaves like a positive emotion and dampens the market response to bad news. If the surprise is generated by the news media, then it behaves like a negative emotion and strengthens the market response to bad earnings news. These findings suggest that pleasant surprises are more likely to be generated by social media whereas the news media is more likely to be the source of unpleasant surprises.

Table 4.10: Impact of Surprise on the Response to Earnings Announcements

			Social + News	Social Media	News Media
Surprise	NUE	Hi surprise	0.02294***	0.00736	0.03674***
		Lo surprise	0.01240***	0.02696***	0.01115*
		Difference	0.01054	-0.0196*	0.02559**
	PUE	Hi surprise	0.04691***	0.05149***	0.04325***
		Lo surprise	0.02606***	0.01944***	0.03027***
		Difference	0.02085**	0.03205***	0.01298
	Company	FEt	-0.01163	0.00905	-0.02706**
		ΔFEt-1 to 1	-0.01482	-0.00159	-0.02382**

See annotation to Table 4.6

4.6 Testing for Robustness

In this section, we provide some detail on the additional checks we conducted to determine the robustness of our reported findings. In particular, we use two important proxies in the paper, one to measure unexpected earnings and the other to measure abnormal returns.

4.6.1 Unexpected Earnings Scaled by Latest Analyst Forecast

In our main analysis, we scaled the unexpected earnings by the absolute value of actual earnings per share. A number of scaling methods are used in the literature, and we repeated the analysis by scaling unexpected earnings by the median consensus analyst forecast and by price. When we repeat our analysis using this different measure of earnings surprise, the results remain quantitatively similar to those that we reported in our main analysis with our main findings being maintained.

4.6.2 Abnormal Returns

The abnormal returns in our main analysis were calculated as the excess return over the market index. We also repeated the analysis using the market model to capture the excess returns and again we found that our major findings were left unchanged.

4.6.3 Impact of Emotions Over Time

Our data covers a period of 20 years over which there have been dramatic changes in the media and especially social media. At our starting date of January 1998, social media was in its infancy with the first recognisable social media site, Six Degrees, being created in 1997, which enabled users to upload a profile and make friends with other users. In 1999, the first blogging sites became popular, creating a form of social media communication that has grown ever since. Hence, the first sub-sample that we have created extends from January 1998 to December 2005 which we suggest as corresponding to the early development phase of (electronic) social media.

YouTube became available in 2005, creating an entirely new way for people to communicate and share with each other across great distances and it was quickly followed in 2006 with both Facebook and Twitter. Hence, we have chosen January 2006 as being a date when social media began to be established as a communication channel. For our purposes, April 2013 is another critical date as it was during this month that the Securities and Exchange Commission (SEC) announced that companies could now use social media as a mechanism for distributing material information to market participants. With this in mind, we have split the period since January 2006 into two sub-periods: January 2006 to June 2013 and July 2013 to December 2017.

We report in Table 4.11 a summary of the impact that the emotion, *Aggregate_Emotion*, has on investor response to postings during each of the sub-periods[23]. Our findings would suggest that the media has been an influence on investor valuation of stocks over our whole sample period as indicated by the fact that both the news and social media have had a direct impact on stock prices in each of the sub-periods. However, the reported coefficients indicate that the impact of *Aggregate_Emotion* has considerably strengthened over the period consistent with the media having a growing impact on investor behaviour over time. When we look at both the absolute level and change of *Aggregate_Emotion* over time, we can see that the news media has dominated social media. However, we can also see that social media's influence is increasing over time.

We obtain quite different results when we examine the influence of both media over time on the market's reaction to bad and good earnings news. Over the first seven years of our 20-year sample, *Aggregate_Emotion* had no influence on how investors reacted to bad earnings news, whereas over the most recent period, *Aggregate_Emotion* played a very important role in dampening the impact that bad earnings news had on security prices. In contrast, *Aggregate_Emotion* has played an important role over the entire sample period in influencing investor response to good earnings news. Somewhat surprisingly though, the strength of this influence marginally weakened over time. Over the whole sample period, it has been *Aggregate_Emotion* emanating from social media that has proved the more important in influencing investor responses to earnings announcements, a finding that is particularly true when it comes to reacting to good earnings news.

In summary, the *Aggregate_Emotion* emanating from both social media and the news has been an influencing factor on investor behaviour over our 20-year sample period. On

[23] The findings for the other emotions lead to similar conclusions as those reported here for *Aggregate_Emotion*.

balance, the level of influence exerted by the media has increased over time with the greatest growth being associated with the *Aggregate_Emotion* emanating from social media.

Table 4.11: The Impact of the Emotions (Aggregate_Emotion) Over Time

Aggregate_Emotion				
	Media source	NUE		
		01/98 – 12/05	01/06-06/13	07/13-12/17
High - Low	Social & News	0.00607	-0.00619	-0.02964**
	Social	0.01043	0.01351	-0.01435
	News	0.03908	-0.04401***	-0.0171
		PUE		
		01/98 – 12/05	01/06-06/13	07/13-12/17
High - Low	Social & News	0.03804**	0.05312***	0.05231***
	Social	0.03898**	0.03167**	0.0294
	News	0.02305	0.0578***	0.04305**
		Direct Effect		
		01/98 – 12/05	01/06-06/13	07/13-12/17
Level	Social & News	0.06248***	0.14063***	0.12012***
	Social	0.02027	0.04008***	0.07979***
	News	0.10750***	0.12336***	0.12354***
Change	Social & News	0.11017***	0.19202***	0.18195***
	Social	0.04849***	0.08581***	0.12927***
	News	0.16777***	0.16802***	0.18909***

The above table reports the results for the following regression.

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t} + \beta_8 \Delta FEt_{i,t-1,1} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ldots \text{(Eq. 4.3)}$$

In addition to the annotation for Table 4.6, here we run our model for three different time-periods for *Aggregate_Emotion* and report the results. The first time-period starts on 1st January 1998 and ends on 31st December 2005. The second time-period starts on 1st January 2006 and ends on 30th June 2013. The third time-period starts on 1st July 2013 and ends on 31st November 2017.

4.7 Conclusion

The story that we tell starts with listings on social media and the news relating to companies and particularly the emotions generated by the choice of words used in these listings. Our primary focus is on examining the extent to which these emotions are absorbed by individuals and their impact on their investment decisions. The proposition is that the tone of these postings will transmit to investors, influence their state of mind, and so affect the way they value stocks and react to information flowing from the company. The data that we use to test this proposition is composed of 10 emotion indices extracted from a textual analysis of the postings on the news and social media. The 10 emotions considered are at three levels of aggregation: (1) *Aggregate_Emotion*, which is the aggregate across the various emotions; (2) aggregate positive emotions and aggregate negative emotions, and (3) each of the 10 individual emotions which consist of four positive emotions (optimism, joy, trust, and love/hate) five negative emotions (stress, gloom, fear, anger, and conflict), and one neutral emotion (surprise). Our design reflects the fact that investors are continually being influenced by many different emotions emanating from the media. In aggregate, these emotions affect the state of mind of investors and so potentially impact on their investment decision-making. The question then arises: does the aggregate of emotions influence the behaviour of investors, and if so, what is the contribution of the various individual emotions?

At the most aggregated level, we find strong evidence to support that *Aggregate_Emotion* has a strong direct impact on market prices plus it influences how investors react to information signals. When we step down one level of aggregation and consider the influence of aggregate positive emotions and aggregate negative emotions, we find that each has an impact similar to *Aggregate_Emotion*. The aggregate of positive emotions directly boosts security prices and the market response to good news. Similarly, aggregate negative emotions directly dampen security prices and the market response to bad news. At this level, however, we do begin to see some deterioration in the strength of the findings compared to those for *Aggregate_Emotion.* This is particularly the case for the impact that aggregate positive and aggregate negative emotions have on investor response to bad earnings news.

In answer to the first question that we posed, we conclude that the evidence relating to the three aggregated emotion measures support the argument that the emotions expressed in the social and news media affect the decision-making of investors. Further, they do this both through a direct channel and an indirect channel through the way they influence the response of investors to information signals. Based on these findings, one would expect that some or all of the individual emotions considered have an influence similar to that of the aggregated measures. This all leads to the following set of questions: are all individual emotions equal in terms of the influence that they have on investors? Are there variations in their influence? Do some emotions exert little or no influence at all?

When we address these questions, we find quite a spread in the degree of variability in the influence of the individual emotions, with some having little or no influence at all. In the case of the four positive emotions, we find that both optimism and joy clearly have a powerful direct and indirect influence on investor decision-making. The influence is of a lesser strength for trust, particularly in terms of the impact that it has on investor response to bad earnings news. For love/hate, we find that this emotion did affect how investors respond through the indirect channel, but it had a weak direct impact on security pricing.

The influence of the individual negative emotions proved to be weaker and even more variable than was found to be the case for the positive emotions. For example, stress, gloom, and conflict all have a direct impact on security pricing, whereas the other two negative emotions have no impact. Stress and gloom each have a strong influence on how investors react to earnings news. In contrast, the influence is much weaker or non-existent across the other three negative emotions. Overall, stress and gloom are the two negative emotions that have the greatest impact on investor behaviour with fear having little or no influence at all. Finally, we have the neutral emotion (surprise) where the extent of the emotion's impact is dependent on where it is sourced. If the surprise emanates from social media, it has a positive effect on how investors react to earnings news. However, if it is sourced from the news media, surprise behaves like a bad emotion in having a negative direct effect on pricing and increasing the extent of the investor reaction to bad earnings news.

We also examined the relative influence of the two media sources and how this might have changed over time. We find that both media sources play a contributing role with the news having a greater influence via the direct channel and social media having the more significant influence via the indirect channel. The stronger direct impact of the emotions generated by the news media is maintained when we examine both aggregate positive and negative emotions. However, we get more mixed results when we examine how these two measures impact on investor reactions to earnings news. For example, for aggregate negative emotions, it is the news that has the greater influence over investor reactions to good news. We have already seen mixed evidence with respect to the extent to which the individual emotions exert influence; equally, we also see mixed evidence in relation to the question of whether social media or the news is the more important source. For example, in the case of joy, the social media has a greater direct effect, but the news media has a slightly greater influence over investor responses to new information. In contrast, we see the reverse for optimism, wherein the news has a greater direct influence, but social media exerts a greater influence on the response to earnings news. When it comes to considering how the influence of the two media sources have changed over time, we first find that the influence of the combined media sources has significantly increased overtime. In the early years of our sample, the news media was definitely the more influential of the two media sources, and its dominance remained at the end of the sample period although the influence of the social media had grown in the intervening years.

Chapter 5: Emotions and Post-Earnings Announcement Drift

5.1 Introduction

In chapter 4, we investigated how 10 different emotions engendered by the news and social media impact on the valuation of a company's stock at the time of the earnings announcement. Our findings show that the two channels that directly impact the valuation of a company are i) the state of mind of the investor conditioned by the emotions transmitted by the media and ii) emotion influencing investor reactions to new information emanating from the company (in our case, earnings announcements). The results of the previous chapter support our proposition and provide empirical validation for Shu (2010) that the prevailing level of emotions expressed in both media sources can lead to investors tending to underreact to earnings announcements. Therefore, it is important to investigate the impact of emotions on investor behaviour in the subsequent period. Again, we continue to use earnings announcements as our test environment because they represent firm news, which investors typically pay close attention to, and occur regularly every quarter but not always on the same calendar day.

Ever since Ball and Brown (1968) presented their work, academics are still trying to explain the post-earnings announcement drift (PEAD) anomaly where stock returns continue to drift in the direction of the earnings surprise beyond the earnings announcement date. Authors either use firm-level or market-level proxies to explain PEAD such as arbitrage risk (Mendenhall, 2004)), liquidity risk (Sadka, 2006), extraneous news around the earnings announcement (D. Hirshleifer et al., 2009), unsophisticated investors (Bartov, Radhakrishnan, & Krinsky, 2000), and options trading (Truong & Corrado, 2014).

Similar to emotions, there are other factors that have been found to shape the environment within which investors make decisions and so impact on stock valuations. Two in particular that have received a fair amount of attention in recent years are market sentiment and market uncertainty. Mian and Sankaraguruswamy (2012) argued that positive sentiment at the time of the announcement generates an asymmetric response to earnings news. (Bird & Yeung, 2012; K. Kim, Pandit, & Wasley, 2016) suggested that the level of market uncertainty at the time of the announcement also influences how they respond to the information. The primary thesis of these studies is that the market sentiment and the market uncertainty prevailing at the time of the information release that can give rise to an initial underreaction with PEAD representing the subsequent market correction to the initial mispricing. For example, they suggest low market sentiment and/or high market uncertainty will result in an initial underreaction to positive earnings announcement with the subsequent upward drift representing the market correction to this initial underreaction. In a similar vein, our findings suggest that low positive emotions and/or high negative emotions will also result in an underreaction to positive earnings news and so provides the potential for a PEAD. The conclusion that we draw from this is that investors do not make decisions in a vacuum but rather in an environment that influences their decisions and so the prices that are set in the market. Individual human emotion is one of several factors that defines this environment and in this chapter, we focus on the contribution that it might make in explaining the PEAD.

While previous studies mostly emphasize that it is the level of sentiment at the time of the announcement that plays a significant role in causing underreaction that leads to PEAD, Bird et al. (2014) argued that it is the prevailing market sentiment and uncertainty over the post-announcement period that plays a much more significant role in explaining PEAD. Following Bird et al. (2014), this study seeks to test the extent to which emotions at the time of the announcement and/or changes in emotions during the post-period contribute to PEAD. For example, we propose that for positive earnings surprise, the biggest drift will come at a time when positive emotions are low at the time of the earnings announcement, and they increase over the post-announcement period. Our findings support this premise where we see that the initial mispricing is not automatically corrected -- rather, the direction of the drift in prices in the post-announcement period is heavily influenced by the direction of emotions during this period.

The study contributes to the literature in many areas. First, while most of the previous literature uses market sentiment as the proxy for emotion, we contribute to the behavioural finance literature by analysing four positive and five negative emotions to demonstrate the relationship between investors' emotions and PEAD. Using nine different emotions will enable us to better understand this anomaly because different emotions of the same valence can have different influences on PEAD. For example, both fear and anger are negative emotions, however, each of them may have a different impact on the investor's decision-making process (Lerner & Keltner, 2001).

Second, the findings also add to the growing literature on the impact of external forces on investors' reactions to earnings news. Past studies have shown that the magnitude of the investors' response to earning surprise can be influenced by external conditions such as market-wide uncertainty (Bird & Yeung, 2012; Williams, 2015), and information uncertainty (Almaskati, Bird, Lu, & Yeung, 2019) at the time of the announcement. Our results validate the findings of Bird et al. (2014) and shows the importance played by the change in emotion over the post-announcement period in explaining the post-announcement drift in prices

Third, this paper also adds to the scant literature that explains the contribution of the news and social media in shaping a company's share price (Griffith et al., 2019). This absence is surprising as the news and social media play an increasing role in our everyday life, and by inference, our decision-making process[24]. While studies have tried to explain the relationship between emotions and financial market reactions using indirect proxies (Hirshleifer & Shumway, 2003; Kamstra et al., 2003), they have been challenged in the literature (Duxbury et al., 2020; Jacobsen & Marquering, 2008). More direct proxies for investor emotion using textual analysis of the news and social media have been developed to explain the impact on the decision-making of investors (Griffith et al., 2019). However, they are limited by a small sample size (Beckers, 2018), and they tend to explain the impact of emotion on initial price reaction (Karampatsas et al., 2018). By pairing a large, novel dataset with recent advances in text processing, we are able to overcome the data challenge inherent in studying investor emotions.

The remainder of the paper is structured as follows: Section 2 provides some background on PEAD. Section 3 explains the data while Section 4 sets out the methodology. Section 5 reports and discusses the findings. Section 6 presents the concluding remarks and discusses possible future work in the area.

5.2 Literature and Background on The Post-Earnings Announcement Drift (PEAD)

The efficient market hypothesis implies that information is quickly impounded into stock prices. However, we see several studies that show that the price adjustment process can be quite slow. Ball and Brown (1968) were the pioneers in documenting an anomaly, post-earnings announcement drift, where the price of the stock drifts in the direction of the earnings surprise during the post-announcement period. The evidence suggests that it can continue for an extended period beyond the time of the release of new financial information, consequently, posing some severe challenges to EMH (Ayers et al., 2011). Therefore, it is not surprising that Kothari (2001) stated that "The post-earnings announcement drift

[24] Please see chapter 2 for a detailed discussion.

anomaly poses a serious challenge to the efficient markets hypothesis. It has survived a battery of tests and many other attempts to explain it away" (p. 196). Fama (1998) termed the PEAD anomaly as "the granddaddy of underreaction events" (p. 286) and apart from being researched extensively, PEAD still exists.

Over the last few decades, we have seen different studies which have tried to explain the delayed price response of stock prices to the earnings information during the post-announcement period. The literature suggests a number of possible explanations for drift. Ball (1978) argued that the drift is due to the model misspecification, whereas Bernard and Thomas (1989) argued that the drift can be attributed to the riskiness of the companies. More recent studies have argued that PEAD can also be explained by high transaction costs. For example, Ng, Rusticus, and Verdi (2008) show that a higher transaction cost on the announcement day corresponds to a weaker initial response and a stronger subsequent drift and that the inverse is true: a lower transaction cost on the announcement day corresponds to a stronger initial response and a weaker subsequent drift. While Chung and Hrazdil (2011) also confirmed that the drift is due to the transaction cost. Cao and Narayanamoorthy (2012), on the other hand, suggested that the drift is not associated with the trading costs when earnings volatility is also taken into consideration.

All explanations for the drift examined to date are attempts to reconcile the evidence on PEAD with the EMH. Another suggestion regarding the inefficiencies in the markets is that the investors make "mistakes" and underreact to both the positive and negative news. Bernard and Thomas (1989) suggest that the delay in price response to the earnings announcement is because of the investors who fail to recognize the implication of future earnings. This suggests that it is individual investors who cause PEAD. For example, Bartov et al. (2000) showed that institutional investors' holdings are negatively correlated with

PEAD returns. Bhattacharya (2001) established that PEAD is caused by small volume trades rather than by large volume trades. Whereas Battalio and Mendenhall (2005) explained in their study that both small (presumably less sophisticated) and large (presumably more sophisticated) traders respond to different types of surprises. Hirshleifer, Myers, Myers, and Teoh (2008) reported that individual investors or some classes of individual investors do not cause PEAD.

Clearly, we are far from getting closure on the factors that drive the continued existence of PEAD. As the literature supports the evidence that we are sensitive to emotions (or moods). A strain of literature has used investors' state of mind as a possible explanation of PEAD. The argument is that the investors' state of mind at the time the new information arrives will cause them to underreact. While one individual's emotions may simply impact their decision making, once aggregated across market participants, emotions (or moods) induced decisions can alter asset prices and move financial markets. We see that the literature has used the state of the weather as a proxy for "market-wide" emotions and demonstrated that weather-induced emotions can move financial markets. For example, Schwarz and Clore (1983) find people reported greater satisfaction with their lives when the survey is conducted in sunny weather than when the weather was overcast and rainy. Sunny weather made individuals happier and can attribute this feeling to better life prospects (Shu, 2010). Saunders (1993) provided corroborating evidence of the influence of weather when found that the negative mood associated with cloudy days lead to significantly lower returns. Conversely, Hirshleifer and Shumway (2003) confirmed stock returns on sunny, cloudless days were above average across the majority of the 26 markets that they studied. Heston and Sinha (2017) studied the impact of sentiment generated using news media and concluded that the level of emotion at the time of the announcement can cause delayed investor response. While the previous studies have used the investor state of mind at the time of the announcement to explain PEAD, the thesis of this paper is that the interpretation that the market places on any information is conditioned by the level of emotion at the time of the information release and the change in the level of emotion over the post-announcement period.

5.3 Data & Method

The sample period extends from the beginning of 1998 to the end of 2017, and the sample is restricted to stocks included in the S&P 500 index. The earnings announcement date and analyst forecasts are sourced from I/B/E/S and Compustat. We get firm-level data from CRSP and market-level data such as VIX from CBOE and we source emotions data from TRMI[25].

The basic model which we use in our study to establish the relationship between stock returns and Positive (Negative) unexpected earnings is:

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ \ldots \ (\text{Eq. } 5.1)$$

where $CAR_{i,t}$ is the cumulative abnormal return for the firm “i” over the post-event window “t” which commences on the second day after the announcement and ends on the 60th trading day after the announcement (i.e., t + 2 to t + 60). PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are positive earnings surprises and 0 otherwise. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of expected earnings. So, if UE>0, PUE = UE, otherwise PUE = 0.

We next want to test the extent to which the reaction of investors is affected by the level of emotion at the time of the announcement and the extent to which emotion changes over the

[25] Please refer to chapter 3 for sources of data and data treatment techniques.

event window. To incorporate this, we expand Equation 5.1 as follows to incorporate emotions:

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t+1,60} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ \ldots$$

(Eq. 5.2)

Here $X1$ is an indicator variable that is equal to 1 where firm "i" makes an earnings announcement at time t and the company's emotion level at t-1 4 pm is above median when all levels of emotions are ranked from low to high; otherwise $X1$ = 0. $X2$ is equal to 1 where there is an increase in the level of the company's emotion level over the post-event window (as measured by the difference between the level of emotion at 4pm t+60 and 4 pm t+1); otherwise $X2$ = 0. FEt-1 is the firm value for the emotion at time 4 pm t-1 (the actual value and not a dummy). $\Delta FEt_{i,t+1,60}$ is the change in the firm value of the emotion between 4 pm t+1 and 4 pm t+60 (the actual value and not a dummy).

For the NUE, β_1 is the coefficient when the emotion is low and decreases over the post-event window. $\beta_1 + \beta_3$ is the coefficient when the emotion is high at the time of the announcement, and it decreases over the post-event window. $\beta_1 + \beta_5$ is the coefficient when the emotion score is low at the time of the announcement, and it increases over the post-event window. Finally, $\beta_1 + \beta_3 + \beta_5$ is when the emotion is high at the start of the event, and it increases over the post-event window.

For the PUE, β_2 is the coefficient when the emotion is low and decreases over the post-event window. $\beta_2 + \beta_4$ is the coefficient when the emotion is high at the time of the announcement, and it decreases over the post-event window. $\beta_2 + \beta_6$ is the coefficient when the emotion score is low at the time of the announcement, and it increases over the post-event window. Finally, $\beta_2 + \beta_4 + \beta_6$ is when the emotion is high at the start of the event, and it increases over the post-event window. We will perform a Wald-test to determine if the coefficients are statistically significant from zero.

5.4 Empirical Results

The focus of this paper is on determining the extent to which the PEAD is influenced by emotions emanating from the news and social media. To analyse this, first we need to address whether there is PEAD in our data. We divide our sample into groups of positive and negative earnings announcements and apply Equation 5.1. The coefficients attached to both NUE and PUE are positive and significant consistent with there being a downward drift in prices after a bad earnings news announcement and an upward drift after a good earnings news announcement. Most of the control variables have the expected sign and are significant.

Table 5.1: An Analysis of Negative and Positive Unexpected Earnings

	CAR (2, 60)
NUE	0.00508**
PUE	0.00597**
Ln (MV)	-0.00709***
BTM	0.07510***
Beta	-0.01002***
VIX	-0.01484***
FQ4	-0.00152***
Loss	0.01938***
Friday	0.00018
Evol	0.00215
Number of observations	46,084
Effects	Yes
SE Clustering	Yes

The above table reported the results for Eq. 5.1. The dependent variable, $CAR_{i,t}$, is the accumulated excess return over the post-announcement period which commences on the second day after the announcement and ends on the 60th trading day after the announcement (i.e., t + 2 to t + 60). The unexpected portion of an earnings announcement is defined as the difference between the actual earnings and the consensus earnings estimate in the month immediately prior to the announcement. We scaled the unexpected portion of the earnings announcement by the actual earnings announced to arrive at our final measure of unexpected earnings. PUE are events where the announced earnings are greater than the consensus analyst forecast earnings. PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are positive earnings surprises and 0 otherwise. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of the consensus analyst forecast earnings. PUE are events where the announced earnings are greater than the expected median analysts' forecast earnings. PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are positive earnings surprises and 0 otherwise. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of expected earnings. The notations ***, **, and * denote statistical significance at the 1, 5 and 10% levels respectively.

In the previous chapter, we found that the magnitude of the initial price adjustment to an earnings announcement is influenced by the level of emotion existing at the time of the announcement. For example, we found that investors will respond less to good earnings news if it is released at a time when positive emotions are low. In such a situation, one might expect that an initial underreaction may provide the room for an upward post-announcement drift as the price is adjusted to take account of the initial underreaction. The second observation that we would make is that any movements in the level of emotions relating to a company during the period after the information release date has been found to cause investors to revisit their initial reaction (Almaskati et al., 2019). The implication here is that an increase in the level of a positive emotion subsequent to a good earnings announcement will cause investors to reassess their initial reaction and return to the markets to further drive up the price of the stock. Putting these two observations together, we suggest that the greatest upward PEAD attributable to emotions is likely to occur as a response to a positive earnings surprise where the announcement is made at a time when positive emotions are low but where the positive emotions increase during the post-announcement period. The obverse of this is that we would expect to see the smallest (or even negative) PEAD to occur as a response to a positive earnings surprise which was announced when positive emotions are high, but which subsequently decline during the post-announcement period. The remaining two situations with respect to a positive earnings announcement being made either at a time when positive emotions are low but which subsequently decreases, or at a time when the positive emotions are high but which subsequently increases, would both be considered likely to contribute to a level of price drift that lies somewhere between the two combinations that we have just discussed.

A similar conversation could be developed to determine the expected outcome in terms of price drift for the other combinations of good and bad earnings news with levels of positive and negative emotions. The expectations with respect to these are to be found in Table 5.2 where a "1" indicates the conditions under which we would expect to see the highest drift while "4" indicates the conditions under which we would expect to see the lowest (or even a reverse) drift. The other two combinations would be expected to be associated with drifts that lie within the two extremes. However, we can further learn something by comparing the two combinations with a "2/3" rating. For example, when looking at the positive emotion/PUE combination, if there is a greater drift for high and increasing as compared to low and decreasing, PEAD is more driven by the behaviour of the emotion during the post-announcement period rather than as a response to any initial underreaction to the earnings announcement.

Table 5.2: Our Expectations with Respect to the Outcome of Results

Direction of **Positive** Emotion Movement Post-Announcement	**NUE**		**PUE**	
	Positive Emotion level at time of announcement		**Positive** Emotion level at time of announcement	
	Low	High	Low	High
Decreasing	2/3	1	2/3	4
Increasing	4	2/3	1	2/3
Direction of **Negative** Emotion Movement Post-Announcement	**NUE**		**PUE**	
	Negative Emotion level at time of announcement		**Negative** Emotion level at time of announcement	
	Low	High	Low	High
Decreasing	2/3	4	2/3	1
Increasing	1	2/3	4	2/3

5.4.1 Aggregate Emotions

Table 5.3 lists the coefficients that indicate the extent to which *Aggregate_Emotion* emanating from the news and social media has influenced the market reaction to both NUE and PUE over the post-announcement period. In the case of NUE we see that there is a significant downward drift in valuations in those instances where *Aggregate_Emotion* decreases over the post-announcement period, both where it was high and low at the time of the announcement. However, the drift is greater when *Aggregate_Emotion* was high at the time of the emotion, suggesting that that it is the downward drift, rather than the level at the time of the announcement, in *Aggregate_Emotion* that pays the bigger role in driving the PEAD that follows an negative unexpected earnings. Interestingly, we see that there is a positive drift after a poor earnings announcement where the earnings is released when *Aggregate_Emotion* is high and where there are further increases during the post-announcement period. These finding suggests that it is the change in the level of emotions rather than its initial level which is likely to be the main contributing factor influencing PEAD.

With PUE, we only see a positive drift in the predicted case where *Aggregate_Emotion* increases during the post-announcement period after being low at the time of the announcement. There is some slight evidence that the market overreacts to positive earnings news which is released when *Aggregate_Emotion* is high at the time of the announcement but subsequently falls as the coefficient on the drift for these circumstances is negative albeit insignificant. The evidence with PUE supports the argument that both the level of *Aggregate_Emotions* at the time of the earnings announcement and the direction it takes in the post-announcement period might contribute to the behaviour of stock valuation in the post-announcement period.

Overall, our findings suggest that *Aggregate_Emotion* does have some indirect influence via the earnings announcement on the path that stock valuations take during the post-announcement period. We have also suggested that *Aggregate_Emotion* will have a direct impact on stock valuations over time. However, when we test for this, we find that PEAD is not affected by either the initial level of *Aggregate_Emotion* or how its value changes over the post-announcement period. We reported in Chapter 4 that both the level of, and direction of the level of, *Aggregate_Emotion* had a positive influence on stock valuations at the time of the announcement, but our current analysis could find no such direct relation of *Aggregate_Emotion* with PEAD. Of course, this does not deny the possibility that some components of the *Aggregate_Emotions* will have a direct impact on stock valuations, a possibility which we will further evaluate below.

Table 5.3: Impact of *Aggregate_Emotion* on PEAD for News&Social Combined

Aggregate_Emotion from News&Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	**0.01727*** **	**0.00714***
Increasing	0.00142	**-0.00871****
Aggregate_Emotion from News&Social (PUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	0.00462	-0.00609
Increasing	**0.01748*** **	0.00677
Level	-0.01412	
Change	-0.00154	

The above table reported the results for Eq. 5.2.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t+1,60} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 5.2)

The dependent variable, $CAR_{i,t}$, is the accumulated excess return over the post-announcement period which commences on the second day after the announcement and ends on the 60th trading day after the announcement (i.e., t + 2 to t + 60). The unexpected portion of an earnings announcement is defined as the difference between the actual earnings and the consensus earnings estimate in the month immediately prior to the announcement. We scaled the unexpected portion of the earnings announcement by the actual earnings announced to arrive at our final measure of unexpected earnings. PUE are events where the announced earnings are greater than the consensus analyst forecast earnings. PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are positive earnings surprises and 0 otherwise. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of the consensus analyst forecast earnings. PUE are events where the announced earnings are greater than the expected median analysts' forecast earnings. PUE is calculated by multiplying the unexpected earning by a dummy variable which takes the value of 1 if there are positive earnings surprises and 0 otherwise. Similarly, a negative unexpected earnings (NUE) event occurs when the earnings just announced fall short of expected earnings. $X1$ is an indicator variable that is equal to 1 where firm "i" makes an earnings announcement at time t and the company's emotion level at t-1 4 pm is above median when all levels of emotions are ranked from low to high; otherwise $X1 = 0$. $X2$ is equal to 1 where there is an increase in the level of the company's emotion level over the post-event window (as measured by the difference between the level of emotion at 4pm t+60 and 4 pm t+1); otherwise $X2 = 0$. FEt-1 = the firm value for the emotion at 4 pm t-1 (the actual value and not a dummy). ΔFEt-1 to t+60 = the change in the firm value of the emotion between 4 pm t+1 and 4 pm t+60 (the actual value and not a dummy). We perform Wald-test to determine if the coefficients are statistically significant from zero. Various control variables and effects were also added. The notations ***, **, and * denote statistical significance at the 1, 5 and 10% levels respectively.

The discussion to date has concentrated on the combined effect of the news and social media. In Table 5.4, we repeat our analysis to help us assess whether there is any difference between both the form and magnitude of the impact that the two media sources have on investor behaviour. In the case of bad earnings news, we find for both media sources that the earnings news contributes to PEAD in all cases where *Aggregate_Emotions* decrease over the post-announcement period. In the case of *Aggregate_Emotions* generated by the news, we found that a decreasing *Aggregate_Emotions* has a much larger impact in cases where *Aggregate_Emotions* are high at the time of the announcement. This finding is consistent with both the level of, and change in the level of, *Aggregate_Emotions* playing an important role in explaining PEAD. However, in the case of *Aggregate_Emotions* generated by social media, the impact on PEAD attributable to changes in the level of *Aggregate_Emotion* is unaffected by the level of *Aggregate_Emotions* at the time of the announcement. What this suggests is that, in the case of emotions generated by social media, the driving force of any relationship between NUE and PEAD is movement in *Aggregate_Emotions* over the post-announcement period. This finding is consistent with the findings discussed above for the *Aggregate_Emotions* generated by the combination of the news and social media where we also found that changes in the level the level of emotions at the time of the announcement played the major role in explaining the PEAD. A comparison of the coefficients across the two media sources suggests that although both play an important role in explaining PEAD associated with bad earnings news, it is the emotions generated by social media that plays the greater role.

When it comes to the response to good earnings news, we also find the expected outcome for both the news and social media that the contribution to PEAD is greatest in those cases where *Aggregate_Emotions* was low at the time of the announcement but subsequently increased over the post-announcement period. In the case of social media, the influence of deceasing *Aggregate_Emotion* on the PEAD is similar irrespective of its level at the time of the announcement, suggesting that changes in the level is the more important influence on the PEAD. In contrast for the news media, we find that a low initial level of *Aggregate_Emotion* influences the PEAD irrespective of the direction followed by the emotions in the post-announcement period. Hence, in the case of emotions generated by the social media. than is the change in emotions, rather than the level of emotions, that plays a far greater role in explaining how emotions contribute to PEAD. Overall, this balances out and so supports the previous finding that both initial level and change in level in *Aggregate_Emotion* contribute to how the combination of the news media and the social media contribute to the PEAD after a good earnings announcement. . Finally, we find that it only changes in the level of emotions generated by the news media that has a direct impact on the PEAD.

Table 5.4: Impact of *Aggregate_Emotion* on PEAD for News and Social Media

Aggregate_Emotion from News (NUE)			Aggregate_Emotion from Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.00760****	**0.01335*****	**Decreasing**	**0.01560*****	**0.01639*****
Increasing	-0.00171	0.00404	**Increasing**	-0.00086	-0.00007
Aggregate_Emotion from News (PUE)			**Aggregate_Emotion from Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.01328*****	**-0.00972****	**Decreasing**	-0.00264	-0.00494
Increasing	**0.01965*****	-0.00335	**Increasing**	**0.01795*****	**0.01565*****
Level	**-0.02981*****		**Level**	0.00078	
Change	-0.01129		**Change**	-0.00075	

See annotation to Table 5.3

5.4.2 Aggregate Positive Emotions

We next break down *Aggregate_Emotion* into the components coming from each of the positive and negative emotions to deepen our insights into the impact that the emotions generated in the news and social media have on investor behaviour. The results for the aggregated positive emotions are reported in Table 5.5. The message is quite clear in both cases: decreasing positive emotions drive PEAD in the case of NUE while increasing positive emotions drive PEAD in the case of PUE. We further see that the relationship between the earnings announcement and PEAD in the case of both NUE and PUE is greater when aggregate positive emotion is low at the time of the earnings announcement. This makes sense for PUE as a low level of aggregate positive emotions should translate into a lower initial reaction to the positive earnings surprise and so the potential for a higher PEAD. However, it makes less sense in the case of an NUE where the low emotions should deliver a higher initial response to the negative earnings news and so leave less potential for a subsequent upward drift. Overall, it would appear that the drift in stock valuation subsequent to an earnings announcement is more due to the movement in aggregate positive emotions in the post-announcement period rather than its value at the time of the announcement. when it comes to the direct impact of aggregate positive emotions on stock valuation. In other words, this provides clear evidence that PEAD is very much influenced by the trend in prevailing emotions over the post-announcement period and is, to a much lesser extent, conditioned by the level of emotions at the time that the information is released. When we consider the direct impact of aggregate positive emotions on stock valuations, we find more evidence to support the importance of changes in the level of positive emotions during the post-announcement that only changes in the level of positive emotions in influencing stock valuations during this period.

Table 5.5: Impact of Aggregate Positive Emotions on PEAD for News&Social Combined

Aggregate Positive Emotions: News&Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	**0.02006***	**0.0147***
Increasing	0.00109	-0.00427
Aggregate Positive Emotions: News&Social (PUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	0.00461	-0.00686
Increasing	**0.01984***	**0.00837***
Level	0.00946	
Change	**0.03252***	

See annotation to Table 5.3

In Table 5.6 we provide information that enables us to differentiate between the impact of the news and social media on investor behaviour. The findings for NUE when we disaggregate positive emotions into those attributable to the social media and those attributable to the news media are consistent with those discussed previously for the when the news and social media are combined. For both media sources there is high correlation between the trend in the emotions over the post-announcement period and the path taken by stock valuations. The situation is quite different with PUE where in the case of the news media, it is low positive emotions at the time of the announcement that drives PEAD, irrespective of the path that positive emotions take in the post-announcement period. This is quite different from the impact of social media where it is high initial emotions further enhanced by low aggregate positive emotions at the time of the announcement that contributes to PEAD. Overall, it is the aggregate positive emotions generated by social media that exercises the greater impact on the PEAD.

Table 5.6: Impact of Aggregate Positive Emotions on PEAD for News and Social Media

Agg. Positive Emotion from News (NUE)			**Agg. Positive Emotion from Social (NUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.01493*** **	**0.01112** **	**Decreasing**	**0.01248** **	**0.01128** **
Increasing	0.00365	-0.00016	**Increasing**	0.00246	0.00126
Agg. Positive Emotion from News (PUE)			**Agg. Positive Emotion from Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.01455** **	-0.00047	**Decreasing**	0.00116	-0.00902
Increasing	**0.01706*** **	0.00204	**Increasing**	**0.02476*** **	**0.01458*** **
Level	0.00210		**Level**	**0.01499***	
Change	**0.03153*** **		**Change**	**0.02517*** **	

See annotation to Table 5.3

5.4.3 Aggregated Negative Emotions

The results, when we analyse the contribution that aggregated negative emotions have on PEAD, are reported in Table 5.7. For NUE, we find that increasing negative emotions over the post-announcement period results in the unexpected earnings making a positive contribution to PEAD, irrespective of whether negative emotions were high or low at the time of the announcement. However, the fact that the coefficient is greater when negative emotions were low at the time of the announcement suggests that the contribution of the change in emotions is greater and it partly reflects an initial underreaction to the bad earnings news. It also suggests that the level of, and changes in the level of, aggregate negative earnings surprise both play an important role in defining the relationship between NUE and PEAD. In the case of PUE, we see that the aggregate negative emotions make the greatest contribution to PEAD under the expected scenario where it starts high and subsequently reduces. Again, this is consistent with the initial market response to the good news being lessened by the high negative emotions at the time of the announcement which leaves the opportunity for a larger subsequent drift fuelled by the reduction in negative emotions. Overall, our findings with respect to aggregate negative emotions suggest that both the initial level of, and change in, emotions over the post-announcement period of the aggregate negative emotions contribute to PEAD.

Table 5.7: Impact of Aggregate Negative Emotions on PEAD for News&Social Combined

Agg. Negative Emotions: News&Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	0.00339	-0.0025
Increasing	**0.01138*** **	**0.00549***
Agg. Negative Emotions: News&Social (PUE)		
CAR {2, 60}	**Lo**	**Hi**
Decreasing	0.00711	**0.01548*** **
Increasing	-0.00243	0.00594
Level	**-0.01953***	
Change	-0.00319	

See annotation to Table 5.3

We analyse the impact of the negative emotions from each of the two media sources and our findings are reported in Table 5.8. There is a difference across the two media sources in how aggregate negative emotions influence the returns over the post-announcement period. In the case of NUE, we see for the news media that low negative emotions at the time of the announcement gives rise to PEAD, irrespective of what path negative emotions take over the post-announcement period. In contrast, it is the path taken by negative emotions during the post-announcement period that determines the impact that emotions have on PEAD, with this influence being greater where the aggregate negative emotions were initially low. The implication here is that for the emotions emanating from the news media, it is only the aggregate negative emotions at the time of the earnings announcement that impact on the relationship between NUE and PEAD. In comparison, for the aggregate negative emotions emanating from social media, both the level of initial emotions and its trend over the post-announcement period influence the role played by aggregate negative emotions in the relationship between NUE and PEAD.

In the case of PUE, there is greater similarity in the impact of the two media sources. For the news media, the influence of the unexpected earnings on PEAD is restricted to what was previously identified as the most likely case where negative emotions were high at the time of the announcement but subsequently fell. For social media, negative emotions were found to influence PEAD in all cases where the negative emotions fell during the post-announcement period with the influence being greater when the negative emotions were high at the time of the announcement. Overall, we find for negative emotions generated by both social media and the news that it is the level of positive emotions at the time of a good earnings news announcement, in combination with the path taken by aggregate negative emotions over the post-announcement period, which determines the relationship between PUE and PEAD.

On balance, the data suggests that it is the negative emotions emanating from social media that have the greater impact on how investors react to earnings news over the post-announcement period. We would come to a similar conclusion when examining the direct consequence of negative emotions for stock valuation with the negative emotions generated from social media having a slightly greater influence on investors than negative emotions arising from the news media. The magnitude of the impact on PEAD is greater for negative emotions emanating from social media for NUE. For PUE, however, the news has a greater impact on PEAD. We find that both the news and social media have a direct impact on corporate valuations.

Interestingly, when it comes to the direct impact negative emotions have on PEAD, in the case of both media sources, it is the level of negative emotions at the time of the announcement that influences PEAD rather than the change in emotions during the post-announcement period. We find that the presence of high negative emotions at the beginning would have already directly suppressed stock valuations, and that path followed by negative emotions over the post-announcement period appears to do nothing to reverse this process.

Table 5.8: Impact of Aggregate Negative Emotions on PEAD for News and Social Media

Agg. Negative Emotion from News (NUE)			Agg. Negative Emotion from Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.00783***	0.00504	**Decreasing**	0.00782	0.00039
Increasing	**0.0078****	0.00501	**Increasing**	**0.01514*****	**0.00771***
Agg. Negative Emotion from News (PUE)			**Agg. Negative Emotion from Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00621	**0.02045*****	**Decreasing**	**0.01303*****	**0.01492*****
Increasing	-0.00365	0.00297	**Increasing**	-0.00612	0.0013
Level	0.00210		**Level**	**0.01499***	
Change	**0.03153*****		**Change**	**0.02517*****	

See annotation to Table 5.3

5.4.4 Individual Positive Emotions

Next, we further disaggregate the emotion scores into the four distinct positive emotions analysed in this study and report our findings in Table 5.9. Overall, we find that each of the positive emotions contributes to how emotions impact on stock valuations over the post-announcement period. That said, the nature of these contributions varies across the different positive emotions. In some cases, the level of emotions at the time of the announcement appears to play the larger role in determining the influence that the earnings surprise has on PEAD. In other cases, the movement in the level of emotions exerts a greater influence. With optimism, it is a reduction in the level of emotion that contributes most to PEAD after good earnings news whereas a low level of optimism at the time of the earnings announcement contributes most to PEAD after a bad earnings number. Interestingly, optimism contributes to an upward drift after bad earnings news when optimism starts high and further increases. This suggests that investors are reacting more to the increase in optimism rather than to the disappointing earnings news. With joy, we have almost the opposite to optimism: an increase in the level of joy drives a positive drift after an unexpectedly good earnings number, while an initially low level of joy contributes to a downward drift after a disappointing earnings number. The magnitude of this contribution is greater where joy further reduces over the post-announcement period.

The impact of trust is similar to that of optimism where it is a reduction of trust that contributes to PEAD after a bad earnings announcement with this contribution being greatest where trust started at a low level at the time of an announcement. In terms of PUE, trust makes a positive contribution to a positive drift after the time of the announcement in the expected case where trust starts low but increases over the post-announcement period. Love/Hate acts in a similar way to joy where it is the upward trajectory in love/hate over the post-announcement period that contributes to an upward drift after a good earnings announcement irrespective of the level of love/hate at the time of the announcement. With NUE, it is the level of love/hate at the time of the announcement that determines the contribution that emotions make to PEAD after bad earnings news. This contribution is independent of the movement in love/hate over the post-announcement period.

Our findings indicate that all four positive emotions play a role in explaining the influence that unexpected earnings have on PEAD. In some cases, the contribution is attributable to the level of the emotion at the time of the earnings announcement while in other cases, it is attributable to the change in the level of the emotion during the post-announcement period. With optimism and trust, we find that contribution is largely due to the change in emotions in the case of investor reactions to disappointing earnings news, but in the case of good earnings news, the contribution is largely owing to the level of emotions at the time of the announcement. All this changes with joy and love/hate, where it is the change in the level of emotions that influence the contribution to PEAD after a disappointing earnings announcement whereas it is the level of emotion that contributes to PEAD after a good earnings announcement. When looking at aggregate positive emotions, we clearly saw that in the case of NUE and PUE, it was the change in emotions that was most associated with the influence of unexpected earnings on PEAD. When we disaggregate positive emotions into its four components, we see that their contribution is much more complex than the aggregate would suggest with each individual emotion having its own peculiarities in terms of how it influences the impact that unexpected earnings have on PEAD.

All of the discussion to date has focussed on the indirect impact that each of the positive emotions has on the drift in prices attributable to the reaction to an earnings announcement. We also analyse the direct impact that emotions have on stock valuations and find, in the case of optimism, joy and trust, that both the level of the emotion at the time of the announcement and the subsequent change in the emotion after the announcement both made (direct) contributions to PEAD. For each of these three emotions, there is a positive relationship between both the level, and change in the level, of the emotion and a positive upward movement in stock valuations. However, for love/hate we found no association between either the level or the change in level and PEAD.

Table 5.9: Impact of Individual Positive Emotions on PEAD for News&Social Combined

Optimism: News&Social (NUE)			Joy: News&Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.01934*** **	**0.01234*** **	**Decreasing**	**0.02257*** **	0.00043
Increasing	-0.00181	**-0.00881** **	**Increasing**	**0.01645*** **	-0.00569
Optimism: News&Social (PUE)			**Joy: News&Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.00750***	-0.00309	**Decreasing**	-0.00107	-0.00137
Increasing	**0.01386*** **	0.00327	**Increasing**	**0.00965***	**0.00935***
Level	**0.00603***		**Level**	**-0.04553*** **	
Change	**0.00645** **		**Change**	**0.02834** **	
Trust: News&Social (NUE)			**Love/Hate: News&Social (NUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	**0.01558*** **	**0.00861** **	**Decreasing**	**0.01052***	0.00403
Increasing	0.00472	-0.00225	**Increasing**	**0.01187** **	0.00538
Trust: News&Social (PUE)			**Love/Hate: News&Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00586	0.00107	**Decreasing**	-0.00411	-0.00585
Increasing	**0.00879***	0.004	**Increasing**	**0.02026*** **	**0.01852*** **
Level	**0.05205*** **		**Level**	-0.00207	
Change	**0.05383*** **		**Change**	0.00792	

See annotation to Table 5.3

We will not report via tables the impact of the four positive emotions emanating separately from the news and social media. However, we will briefly comment on the more interesting insights that they provide. Given that the results reported in Table 5.9 and those discussed above represent the consequences of the combined impact of the news and social media, it would not be surprising to find that each media source contributes to various degrees to the combined impact. However, it is noticeable that the combined impact is sometimes more in tune with one or other of the two media sources. In particular, we find that the overall findings with respect to optimism and love/hate are more driven by the news whereas those for joy and trust are more driven by social media.

5.4.5 Individual Negative Emotions

The results for each of the individual negative emotions are weaker than those for the individual positive emotions plus they follow a less discernible pattern. We will examine the findings reported in Table 5.10 for each of the negative emotions before drawing some overall conclusions. Starting with stress, we find that it has no impact on how NUE influences PEAD, but for PUE, we find evidence to suggest that PEAD is influenced in all cases where stress is high at the time of the announcement with the impact being greater if stress reduces over the post-announcement period. In contrast, we find that gloom does influence PEAD after a negative earnings surprise in all cases where gloom increases over the post-announcement period, and these findings hold irrespective of the level of gloom at the time of the announcement. Gloom is the only negative emotion associated with a reversion in stock valuations in the case of NUE which occurs when gloom starts low and decreases further over the post-announcement period. There is only very weak evidence of gloom influencing the relationship between PUE and PEAD with this occurring in the somewhat surprising instance where gloom starts low and subsequently increases.

With conflict, a very weak finding emerges of a drift after a negative earnings surprise in the somewhat surprising instance where conflict is high at the time of the announcement. In the case of conflict and PUE, we find that the earnings announcement exercises a strong influence on PEAD in the expected case where conflict starts high and then decreases over the post-announcement period. The indirect impact of fear on PEAD behaves very much as predicted, with the downward drift after a negative announcement occurring when fear is low at the time of the announcement. The upward drift after a positive earnings surprise occurs when fear decreases during the post-announcement period, with this drift being greater when fear was high at the time of the announcement. Finally, with anger, we find limited evidence and some quite counter-intuitive results. We find that anger contributes to a PEAD associated with negative earnings news when anger is low at the time of the announcement and particularly when it trends even lower in the post-announcement period. When it comes to PUE, we find surprisingly that an upward drift in valuations in the post-announcement period to be associated with a rise in the level of anger. Overall, the findings are more consistent with anger behaving more like a positive emotion than a negative emotion.

This is an appropriate point on which to reflect to our findings for aggregate negative emotions reported in Table 5.7. Our findings are basically in line with the expectations we held for negative emotions to impact on the relationship between an earnings surprise and PEAD. For NUE, we find that increasing negative emotions during the post-announcement period contributed to downward drift in stock valuations in the period subsequent to an earnings announcement, and this relationship was stronger if the negative emotions were relatively high at the time of the announcement. For PUE, we found that negative emotions contributed to the upward drift in stock valuations under the expected conditions that negative emotions were high at the time of the earnings announcement but subsequently fell. Although the findings for the individual negative emotions identify many situations which suggest that they contribute to PEAD, the way that this occurs varies widely. There is not one case where any of the individual negative emotions impact on PEAD after a NUE in the same way identified for the aggregate of these emotions. Gloom comes closest with the PEAD being influenced by increasing gloom over the post-announcement period, but in this case, the influence is greatest where gloom was high at the time of the announcement. In contrast, there are three emotions (stress, conflict, and fear) that contribute to PEAD in terms of the reaction to good earnings news in a way similar to the contribution of aggregate negative emotions. These three emotions contribute to the relationship between the earnings announcements and the post-announcement drift in stock valuations when an individual emotion takes on a high value at the time of the announcement, but which subsequently declines over the post-announcement period. Finally, of the negative emotions, the one that behaves most peculiarly is anger which appears to behave more like a positive emotion than a negative emotion.

The discussion above concentrated on how emotions impacted on the market behaviour attributable to earnings announcements in the post-announcement period. We have also discussed and tested for an effect where the emotions directly impact on stock valuations. We see only limited evidence of this direct effect occurring, with there being only two negative emotions (stress and anger) where the level of the emotion impacted on PEAD and no cases where changes in the level of emotion impacted on PEAD. For both stress and anger, there is a negative relationship between their level and PEAD, indicating that they put downward pressure on stock valuations.

Table 5.10: Impact of Individual Negative Emotions on PEAD for News&Social Combined

Stress: News&Social (NUE)			Gloom: News&Social (NUE)		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00357	0.00489	**Decreasing**	**-0.00845****	-0.00548
Increasing	0.00399	0.00531	**Increasing**	**0.01311*****	**0.01608*****
Stress: News&Social (PUE)			**Gloom: News&Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00280	**0.01286****	**Decreasing**	0.00710	0.00184
Increasing	-0.00235	**0.00771***	**Increasing**	**0.00819***	0.00293
Level	**-0.01747****		**Level**	-0.00701	
Change	0.00202		**Change**	0.00877	
Conflict: News&Social (NUE)			**Fear: News&Social (NUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00299	**0.00652***	**Decreasing**	0.00174	-0.00497
Increasing	0.00378	**0.00731***	**Increasing**	**0.01321*****	0.0065
Conflict: News&Social (PUE)			**Fear: News&Social (PUE)**		
CAR {2, 60}	**Lo**	**Hi**	**CAR {2, 60}**	**Lo**	**Hi**
Decreasing	0.00213	**0.01477*****	**Decreasing**	**0.01471****	**0.02043*****
Increasing	-0.00603	0.00661	**Increasing**	0.0005	0.00622
Level	-0.00196		**Level**	-0.01673	
Change	-0.00719		**Change**	0.00404	
Anger: News&Social (NUE)					
CAR {2, 60}	**Lo**	**Hi**			
Decreasing	**0.01547****	0.00736			
Increasing	**0.0102****	0.00209			
Anger: News&Social (PUE)					
CAR {2, 60}	**Lo**	**Hi**			
Decreasing	-0.00002	-0.00056			
Increasing	**0.01253****	**0.01199****			
Level	**-0.03366***				
Change	-0.01730				

See annotation to Table 5.3

Again, for the negative emotions, we analysed the impact of the emotions generated by the news and social media respectively. We concluded from our analysis of the emotion scores calculated for the combination of the news and social media that each of the negative emotions influence PEAD but that the nature of this influence varied significantly across the five negative emotions. We find even greater variation when we separately consider the emotions generated by the news and social media, making it difficult to conclude whether one of the media sources had a greater influence than the other. The news media appears to exert a greater influence in relation to the emotion of stress whereas social media has a greater influence in the case of gloom and fear. Where anger is concerned, its influence seems more like that of a positive emotion when it emanates from the news media. When anger emanates from the social media, its behaviour is more in keeping with what one would expect from a negative emotion.

5.5 Conclusion

In this chapter, we study the impact that emotions have on stock valuations over the post-announcement period. We sought to identify whether emotions play a role in explaining the PEAD and, if so, to establish the nature of the relationship between emotions and the PEAD.

We start off with an *Aggregate_Emotion* measure that is the aggregation of our four positive emotions and five negative emotions. We see evidence to suggest that aggregate emotions contribute to a significant negative drift after negative unexpected earnings, provided that aggregate emotions are decreasing during the post-announcement period. As the strength of this relationship is greater when the aggregate emotions start low, this suggests that it is the direction of the emotions during the post-announcement period that matters most in determining the contributions that aggregate emotions make to PEAD. In addition, we see a positive drift following a positive earnings surprise when the *Aggregate_Emotion* is low at the time of the announcement, and it increases over the post-announcement period. Emotions have previously been found to contribute to the market underreaction to earnings news and our findings in this paper confirm that emotions continue to play a role in determining how the market reacts to earnings news in the post-announcement period.

We further break down the *Aggregate_Emotion* category into aggregate positive and aggregate negative emotions. Consistent with our initial finding, we see that both positive and negative aggregate emotions continue to play a significant role in generating PEAD. In the case of positive aggregate emotions, the initial level of, and changes in the level of, positive emotions are clearly important contributors to PEAD, with the latter being of greater relative importance. With aggregate negative emotions, again, the initial level of emotions and change in levels of emotion contribute to PEAD, although it is difficult to distinguish between the relative importance of the two characteristics.

We then study the impact of individual emotions on PEAD. It is clear that all of the positive emotions impact on PEAD, but there is a large variation in the form of the relationship between each of the individual emotions and the PEAD. For some emotions, it is the level of emotions at the time of the relationship that is the more important in influencing the PEAD, while in others it is the path taken by the emotion over the post-announcement period. We see more mixed results when it comes to the negative emotions with no single negative emotion contributing to PEAD across all the dimensions. One extreme example is anger, which displays more the characteristics of a positive emotion rather than a negative emotion. Finally, we find significant variation in the influence of the two media sources. For example, with the positive emotions, we find that the impact of optimism and love/hate are more driven by the news media whereas the impact of joy and trust are more driven by social media.

The post-earnings announcement drift is one of the longest surviving market anomalies and much effort has been devoted to identifying the factors that cause it to persist. In this chapter, we report on research that confirms that human emotions are yet another factor that play a role in explaining the existence of the PEAD. Further, on balance we find that it is the path taken by emotions during the post-announcement period rather than the level of emotions at the time of the announcement that plays the greater role in explaining the relationship between the earnings announcement and the PEAD. We saw in the previous chapter that emotions impact on pricing reactions to earnings news, raising the distinct possibility of being a key source of mispricing in markets. The fact that we have now found that the level of emotions over the post-announcement period continues to influence the impact of past earnings announcements on stock valuations suggests that prices might take a long time to, or may not ever, adjust to reflect the true implication of past earnings news.

Chapter 6: The Art of Investing on Emotion

6.1 Introduction

For many years, market observers and investment professionals have tried to come up with investment strategies that would exploit the market mispricing to generate superior returns. Several factors such as book-to-market, low risk, going-concern, and momentum (Ali, Hwang, & Trombley, 2003; Chan, Jegadeesh, & Lakonishok, 1996; Detzel & Strauss, 2018; Fama & French, 1992; Kausar, Taffler, & Tan, 2009; Taffler, Lu, & Kausar, 2004) have been used to exploit mispricings to generate profitable investment strategies. In the past 10 to 15 years, financial markets have become more sensitive to news (Uhl et al., 2015) and, along with other factors, investor sentiment plays an important role in shaping stock prices (Baker & Wurgler, 2006). As the media serves as a powerful way for users to share information, it acts as a useful medium to capture investor emotions (Sul, Dennis, & Yuan, 2017). Although empirical studies have considered the impact of the news and social media on stock prices (Antweiler & Frank, 2004; Edmans et al., 2007), it was the ground-breaking work of Tetlock (2007) that utilised textual analysis of news articles to demonstrate that the market underreacts to negative words in news articles. Building on this work, Tetlock et al. (2008) developed an investment strategy using negative words in the news media that would earn them positive annualized returns (23.17%) before trading cost and a negative annualized return (-2.71%) after considering trading costs.

Several studies have found evidence to suggest that emotions engendered by the news and social media can be used to predict stock returns. Leinweber and Sisk (2011) conducted a study that used data from 2003 to 2010 and concluded it is possible to formulate profitable trading strategies based on news sentiment. Uhl et al. (2015) obtained the news sentiment data from 2003 to 2013 and concluded that it can be used to predict stock returns. Heston and Sinha (2017) studied a dataset of more than 900,000 news articles and concluded that a news sentiment-based investment strategy can generate an excess return of 2.15% over a 13-week window. Previous studies have also examined whether the emotions engendered by social media (mostly Twitter) can be used to predict stock returns. Oh and Sheng (2011) examined 200,000 StockTwits to create a "bullishness" index for each stock. They concluded that the 5-day rolling average of this index was effective in predicting movements in the stock prices. Sprenger, Tumasjan, Sandner, and Welpe (2014) used machine-learning to create a "bullishness" index using social media and concluded that stocks tweets have a predictive power of stock returns for several days later. H. K. Sul et al. (2017), while studying the impact of sentiment engendered in social media, concluded that sentiment in tweets can be used to generate a profitable investment strategy that can earn an annualized return of 15.65% for a 10-day holding period.

These studies mostly focus on the level of emotions at the time that when then the information becomes available. We enhance this by attempting to incorporate into our strategy, information on the path taken by emotions during the holding period. Our findings reported in Chapter 4 establish that emotions affect how investors respond to earnings announcements. In particular, we establish that that there will be a lower reaction to good (bad) earnings news released at a time when positive emotions are low (high) and/or negative emotions are high (low). This raises the possibility of an underreaction to earnings news and so benefiting from any subsequent correction in pricing. The findings reported in Chapter 5 support the expectations that one might be able to benefit from such a correction in pricing. We find some instances where the level of emotions as at the time of the emotions provides some explanation for the often-quoted PEAD. However, we find strong evidence to suggest that the drift in prices after the announcement is more influenced by the path that emotions follow over the post-announcement period.

The implications of our findings are that a strategy designed to exploit any mispricings introduced due to the influence of human emotions would incorporate both the level of emotions at the time of the earnings announcement and the path followed by emotions during the post-announcement period. Of course, it is not obvious how we can incorporate into any strategy the path followed by emotions in the period after the announcement as this path is unknown at the time of the announcement when the decision is made as to what stocks should be included in the long and short portfolios. We overcome this obstacle by incorporating the path followed by emotions into our strategy as a signal to determine when the initial transactions should be reversed. We discuss both the features, and performance, of the strategy later in the chapter.

In Section 2 of the paper, we discuss the data and method. Section 3 outlines the major findings in our previous two studies that provide insights into how our knowledge of emotions might be used in designing an investment process. Section 4 is the centrepiece of the paper as it outlines the development of an active investment process that exploits the impact that human emotions have on investment returns. Finally, we use Section 5 to provide some summary comments on our major findings.

6.2 Data

The sample period extends from the beginning of 1998 to the end of 2017, and the sample is restricted to stocks included in the S&P 500 index. The information regarding actual earnings and financial analysts' earnings forecasts is gathered from the IBES database. The accounting data, including reported earnings, is obtained from the CRSP/COMPUSTAT merged database and sourced through WRDS. The return and price data for the equity market were obtained from CRSP and sourced through WRDS.

Furthermore, we source the data on nine distinct emotions (we omit surprise) from the Thomson Reuters MarketPsych Indices (TRMI) database, which extends back to 1998 from which we construct three additional emotion measures: aggregate positive emotions, aggregate negative emotions, and aggregate emotions, which is the sum of the positives and negatives.

6.3. Trading Strategies

The findings in the previous two chapters suggest that emotions may distort stock valuations and provide a means of identifying which stocks will perform either well or poorly in the immediate future. Hence our focus in developing a strategy will be on using emotion scores to determine what stocks to be included in one or other of our portfolios, and to provide an indication as to when we want to remove a particular stock from our portfolio.

We will know briefly review the findings reported in Chapter 4 and 5 in order to identify the particular insights that we can draw from these findings that will assist us in deriving an investment strategy.

6.3.1 Insights from Chapter 4

While looking at the positive emotions, we find that higher positive emotions are associated with higher stock valuations. More importantly, we see that good earnings news has a lower impact on stock valuation when it is released at a time when positive emotions are low. Similarly, bad news has a smaller effect on stock valuations when it is released at a time when positive emotions are high. We identify parallel findings when it comes to negative emotions with bad earnings news having a smaller impact on stock valuations if it is released at a time when negative emotions are low and/or positive emotions are high.

What important insight do we obtain (if any) from these findings when it comes to designing an investment process? The answer is that it has the potential to provide us with insights into where there might have been an underreaction to earnings news which, in turn, might identify the possibility of profiting from any subsequent market correction. One insight is that investors are more likely to underreact to good earnings news when it is released at a time when positive emotions are low and/or negative emotions are high. The parallel insight is that investors are more likely to underreact to bad earnings news if it is released at a time when positive emotions are high and/or negative emotions are low. These findings provide insights into what stocks should be included in our portfolios, namely purchasing good earnings news stocks if they release earnings when positive emotions are low and/or negative emotions are high, and to short-sell bad earnings news stocks when their earnings are released at a time when positive emotions are high and/or negative emotions are low.

6.3.2 Insights from Chapter 5

Chapter 5 is similar to the first empirical study in that it examines the impact that emotions have on stock valuations. In this case, however, the period studied is the 60 trading days after an earnings announcement (basically up to the release of the next earnings number). The major focus of the study reported in this chapter is to determine the extent to which the level of emotion at the time of the announcement and/or the change in emotions over the post-announcement period play a role in determining the performance of stocks the post-announcement period. The strategy suggested by the first study is silent on the importance of future movements in emotions in determining the performance of stocks in the period after the announcement.

We find that an increase in positive emotions over the post-period combined with low emotions at the time of the announcement results in a significant increase in stock prices for companies announcing good earnings news. What is important is that, by itself, low emotions at the time of the announcement may not be sufficient to generate significant positive added value during the post-announcement period. We study this by first evaluating a strategy purely based on the level of emotions at the time of the announcement which will inform us of the importance of incorporating into the strategy, information on the future path taken by emotions. Our findings with respect to bad earnings news are similar suggesting that the path taken by bad emotions during the post-announcement period may play an important role in determining the performance of these stocks during this period. Hence, we will need to give thought as to whether we need to incorporate into our strategy information on the future path of bad emotions.

The problem that we face is that at the time of the earnings announcement when we are determining those stocks to include in our long and short portfolios, we have no information on the path taken by emotions over the post-announcement period. Hence, the level of emotions before the earnings announcement (at 4 pm t-1) is the only emotions information that we will incorporate into the decision as to what stocks to buy/sell short, However, the possibility is to see how emotions evolve subsequent to the earnings announcement and to use this information to the appropriate time to divest the portfolio of particular stocks.

6.3.3 Implications for Efficient Pricing

Before we move on to discuss how we use the insights from these studies to design a profitable investment process, it is interesting to reflect on their implications for market efficiency. The fact that the reaction of stock prices to the release of information can be influenced by emotions is at variance with the Efficient Market Hypothesis (EMH). In chapter 4, we saw that emotions could cause an underreaction to the release of earnings news with a common belief being that the underreaction will be quickly corrected. The major finding in chapter 5 is evidence to suggest that there is no automatic correction to the initial mispricing with the direction that stock valuation takes during the post-period being influenced by the direction that emotions take during this period.

There is similar evidence in previous studies to suggest that both the market reaction to earnings announcements and its performance during the post-announcement period is also conditioned by both the level of market uncertainty and market sentiment prevailing at the time of an earnings announcement and the path that they take in the post-announcement period (Bird et al., 2014). We postulate that the prevailing environment (e.g., the aggregate of emotions, uncertainty, sentiment, and possibly other factors) plays a continuing role in influencing investors and so stocks valuations. If this environment changes, then so do market prices but this is somewhat independent of any "mistakes" that the market has made in the past. In summary, this suggests that there is no automatic correction for previous investor errors but rather, a market that is always at the mercy of the environment in which investors are making decisions, with human emotions being an important component of this environment.

6.4 Where Does this Leave Us with the Development of an Investment Strategy?

The two major insights we take from the two previous papers are:

- It is the level of emotion at the time of the earnings announcement that affects how investors react to earnings news at the time of the announcement.
- The change in emotions over the post-announcement period further influences stock valuations during this period.

Armed with these insights, we commence the pursuit of a profitable investment strategy. We report our findings for three such strategies in Table 6.1. We describe the first strategy as the **index**, and it involves purchasing the S&P 500 index each time a company makes an earnings announcement and then holding the index for 60 trading days. We do this for six sub-samples: all "good" news announcements, above-median good news announcements, below-median good news announcements, all bad news announcements, above-median bad news announcements, and below-media bad news announcements[26]. The annualised returns across each of these index portfolios lie in the narrow range of 11.6% and 11.8%. These portfolios provide a good reference point against which to compare other strategies, as they represent the return on a strategy that uses no information relating to the nature of the earnings announcement or the prevailing emotions but acquires stocks and disposes of them at the same time as in all of the other strategies.

We then move on to what is described as the **benchmark** portfolio, which incorporates into the strategy information relating to the announcement but does not incorporate any information relating to emotions. In this case, shares in companies that make the announcement are purchased if it is a good news announcement or sold-short if it is a bad news announcement with the transaction being reversed after 60 trading days. The annualised returns for this strategy are reported in Table 6.1. We see for good news, the returns are much higher than is the case for the index portfolios, while for bad news, they are lower than for the index strategy. Both findings are consistent with the post-earnings announcement literature that suggests a continuing drift after the announcement. A strategy of purchasing shares in companies with good earnings news and shorting stocks in companies with bad earnings news and reversing the positions after 60 trading days realises a weighted annualised return of 17.01%[27]. However, an even more striking finding is that this annualised return increases to 20.90% if the strategy is restricted to trading in stocks

[26] All the sub-samples and strategies are adjusted for the look-ahead bias. Please see chapter 3 section 3.3.10 for more details on the adjustments for look-ahead bias.
[27] The long portfolio has annualised returns of 17.58% while the short portfolio has annualised returns of 10.83% and the weighted return on the long-short portfolio is 17.01%. For explanation of weighted returns of a long/short portfolio, please refer to Chapter 3 section 3.3.8.

that have above-median good and bad news companies[28]. Thus, restricting our strategy to only investing/shorting stocks that represent the more extreme side of unexpected earnings increases annual performance by almost 4%. This provides a very useful insight as to where we might look when developing a strategy that incorporates emotions.

None of the strategies discussed to date have utilised any information on emotions. We have previously seen that stocks will underreact to news when positive and negative emotions are low at the time of the announcement. What we do is extend the benchmark strategy by now only purchasing companies that announce above average good earnings news if, at the time, their positive emotions are in the bottom quartile. Similarly, we only sell short stock in companies that announce above-medium bad earnings news if, at the time, their negative emotions score is in the bottom quartile. In both cases, we reverse the trades after 60 trading days. This expanded strategy produces a weighted return from the long-short strategy of 20.06%[29], which is almost 1% less than the return that is achieved from the strategy that incorporates no information on emotions (20.90%). This is a very important finding as it confirms that expanding the strategy to take account of any underreaction to earnings announcements caused by the prevailing emotions at the time fails to enhance the performance of the investment strategy, even though these emotions impact on stock valuations through both the direct and indirect channels.

[28] In this case, the annualised long portfolio return is 21.31% while the annualised short portfolio return is 10.21% and the weighted return on the long/short portfolio is 20.90%. For explanation of weighted returns of a long/short portfolio, please refer to Chapter 3 section 3.3.8.
[29] Th return on the long portfolio is 20.73% while that on the short portfolio is 7.31%, resulting in a weighted return on the long-short portfolio of 20.06%.

Table 6.1: Returns Where We Reverse the Transactions at the End of T60.

Aggregate Positive Emotions		Index	Benchmark	Lo **Positive** Emotions
		% pa	% pa	% pa
Good News	All	11.78	17.58	17.10
	High	11.58	**21.31**	**20.74**
	Low	11.78	12.46	12.32
Bad News	All	-11.59	-10.53	-10.38
	High	-11.59	-9.91	-8.30
	Low	-11.59	-10.73	-14.05

Aggregate Negative Emotions		Index	Benchmark	Lo **Negative** Emotions
		% pa	% pa	% pa
Good News	All	11.78	17.85	19.06
	High	11.58	**21.27**	**20.73**
	Low	11.78	13.01	15.85
Bad News	All	-11.59	-10.83	-10.71
	High	-11.59	**-10.21**	**-7.31**
	Low	-11.59	-10.86	-12.64

We first create 6 portfolios based on unexpected earnings. We divide both the positive (good news) and negative (bad news) unexpected earnings into all, above(high)- and below(low)-median at the time of the announcement. This involves us having a measure of the median value for both PUE and NUE. We avoid a look-ahead bias by only using data from past announcements when specifying the median. Although we have data from January 1998, we do not start forming portfolios until January 2003 and so we have five years of data to calculate the initial medians with subsequent medians being determined using an expanding window. For **Index**, we purchase the S&P 500 index each time a company makes an earnings announcement and then holding the index for 60 trading days. We find the annualised returns using the following formula

$$APR_{i,t} = (((IV_t \ / \ IV_{t-1}) \ ^\wedge \ (12 \ / \ n)) - 1) * 100 \ldots \text{(Eq. 13)}$$

where $APR_{i,t}$ is the annualised portfolio return for the portfolio "i" at the time "t". IV_t is the index value at the end of 2017, whereas, $IV_{t-1} here$ is the index value at the beginning of 2003. n is the number of months from the beginning of 2003 to the end of 2017.

For each portfolio "i" of the **benchmark**, we hold the stock based on the unexpected earnings, however, the stocks do not incorporate any information related to emotions. We buy the stock if earnings announcement is positive and short sell if earnings announcement is negative with transactions being reversed after 60 trading days. We calculate the daily stock return of each stock held in the portfolio "i" using the following formula.

$$SR_{i,t} = \frac{P_{t1} - P_{t0}}{P_{t0}} \ldots \text{(Eq. 11)}$$

where SRi,t are stock returns at the time 't', for the company 'i', P_{t0} is the adjusted closing price of the previous trading day, and P_{t1} is the adjusted closing price of the current trading day. Next, for each portfolio "i" of the benchmark, we create an index that starts at 100 on the first trading day of January 2003. Then each subsequent trading day, the value of the index either increases or decreases based on the stock returns held in the portfolio "i" using Eq. 12. For example, if the return on the portfolio "i" at time "t" is 10% (-10%) then the index will increase(decrease) to 110(90).

$$PR_{i,t} = 1 + \frac{\sum_{t=t_0}^{t1} SR_{i,t}}{\text{number of stocks at time "t"}} \quad \ldots \text{(Eq. 12)}$$

where $PR_{i,t}$ are portfolio returns at the time 't', for portfolio 'i'. For the short portfolio, we multiply SRi,t with -1. We than annualise the benchmark returns using Eq. 13.

We follow the same process as benchmark for the **strategy**, however, in addition to the filters based on the unexpected earnings, we purchase companies that announce good earnings news if, at time 4 pm t-1, their aggregate positive emotions are in the bottom quartile. Similarly, we only sell short stock in companies that announce bad earnings news if, at time 4 pm t-1, their aggregate negative emotions score is in the bottom quartile. As we restrict our investments to stocks whose emotion scores fall into the bottom quartile. So, we need to know the breakpoint for the bottom quartile by emotion in order to implement the strategy. Again, we avoid the look-ahead bias by using the holdout period of five years to calculate the initial break point which we then update using an expanding window.

Given that we have established that we cannot simply rely on information on the level of emotions at the time of an earnings announcement as the basis for developing a profitable investment strategy, our attention now turns to the insight we obtain from the study reported in the previous chapter: that it is the change in emotion over the post-announcement period that strongly influences the path taken by stock valuations during this period. The problem is that we cannot directly utilise this finding in our analysis as, at the time when we are trading, we do not know what will happen with emotions during the subsequent period. In a bid to benefit from this insight, we introduce another rule where trades are reversed before the end of the 60-trading day holding period once the emotion score moves by more than a pre-specified amount. This pre-specified amount is based on a certain percentage of the standard deviation of the movement of the emotion score. The trigger that we initially use to trigger the earlier reversal of the transaction is that a stock will be sold/bought back if the emotion score moves by an amount equal to 100% of the standard deviation of the emotions score. The strategy for the long portfolio then becomes:

Buy stocks at the time of an above-median positive unexpected earnings announcement if, at that time, their positive emotions score is in the bottom quartile. Reverse this trade either when the emotions score has moved up by an amount equal to the standard deviation of the positive emotion score, or after 60-trading days, whichever occurs first.

The strategy for the short portfolio is similar:

Short stocks at the time of an above-median negative unexpected earnings announcement if, at the time, their negative emotions score is in the bottom quartile. Reverse this trade either when the emotions score has moved down by an amount equal to the standard deviation of the negative emotion score, or after 60-trading days, whichever occurs first.

The results of this strategy are reported in Table 6.2 and compared to the results (already reported in table 6.1) where there is no trigger for an early reversal of the initial transaction. The improvement in the performance for both the long and short portfolios is quite dramatic with the annualised performance of the weighted long/short portfolio being 29.60%, which is about 50% higher than for the similar strategy but without any trigger for an early closing of both long and short positions.

Table 6.2: Results Using 100% of SD as the Trigger for T60

Aggregate Positive Emotions		Index	Benchmark	Lo/Hi **Positive** Emotions
		% pa	% pa	% pa
Good News	All	11.78	18.01	21.21
	High	11.58	**21.14**	**30.85**
	Low	11.78	13.39	12.78
Bad News	All	-11.59	-11.737	2.72
	High	-11.59	-11.00	13.83
	Low	-11.59	-11.66	-9.29

Aggregate Negative Emotions		Index	Benchmark	Lo/Hi **Negative** Emotions
		% pa	% pa	% pa
Good News	All	11.78	18.01	20.99
	High	11.58	21.14	25.35
	Low	11.78	13.39	13.88
Bad News	All	-11.59	-11.737	2.55
	High	-11.59	**-11.00**	**5.10**
	Low	-11.59	-11.66	-10.32

For Index and Benchmark, please see the annotation of table 6.1. For strategy, similar to the annotation of table 6.1, we buy the stock if earnings announcement is positive and emotion is in the bottom quartile at 4 pm t-1, and short sell if earnings announcement is negative and emotion is in the bottom quartile at 4 pm t-1. However, instead of reversing all the transactions after 60-trading days, we reverse the transaction before the end of the 60-trading day holding period once the emotion score moves by more than a pre-specified amount. For the above results, this pre-specified amount is based on a 100% of the standard deviation (SD) of the movement of the emotion score. We use this 100% of the SD as trigger for buying/selling stocks. Again, we need past data to determine this standard deviation which is another potential source of look-ahead bias. Having a five-year holding period from 1998 to 2002 provides the data to calculate the initial standard deviations which are then updated using an expanding window. If the emotion score of a particular company does not move by this trigger value, we reverse the transaction at the end of 60th trading day.

The question then arises: can one do even better? To address this, it is enlightening to reflect on the moving pieces in the investment strategy that we have developed to date:

1. What measure of emotions should be used?

Currently, we are using aggregate positive emotions for the long portfolio and aggregate negative emotions for the short portfolio.

2. What do we define as high and low emotions?

Currently, we are using the bottom quartile of emotions at the time of the news release.

3. What is "high" and "low" good and bad news?

Currently, we are using above and below-median unexpected earnings.

4. What should be the holding period?

Currently, we are using 60 trading days.

5. What is the appropriate trigger?

Currently, we are using 100% applied to the standard deviation of the emotion score.

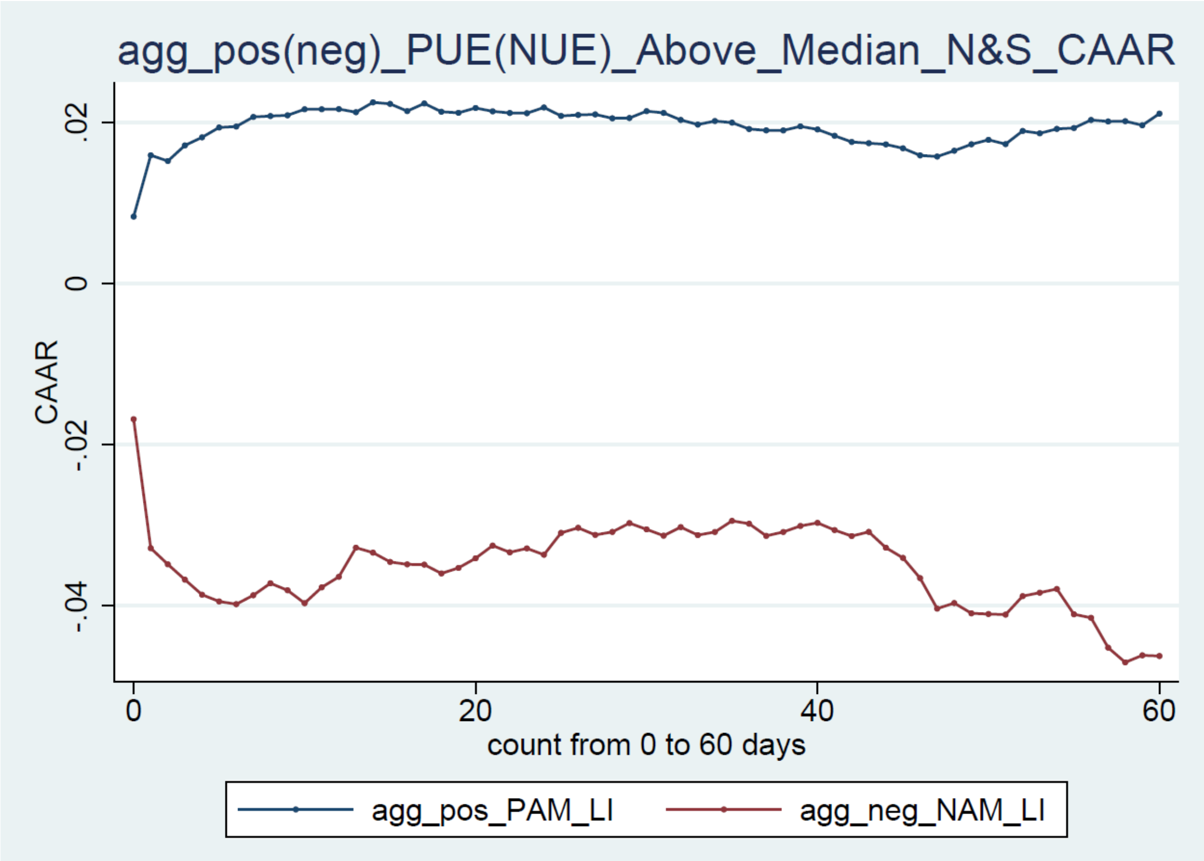
6. What should be our rebalancing strategy?

Currently, we are assuming that we will rebalance the portfolio holdings to equal weights at the end of each day.

For the present, we will continue to use aggregate positive and aggregate negative emotions in our analysis and to continue to rebalance to equal weights. Further, we have reason to believe that it is appropriate to use the median when splitting up good and bad earnings and quartiles as the split between high and low emotions. However, we do see value in introducing different selling triggers and different holding periods. We do get evidence to support this by examining Figure 6.1 which provides us with the cumulative abnormal returns generated by our existing strategies (without triggers) for holding periods up to 60 days. The results for the long portfolio suggest that most of any outperformance is generated in a relative short period of time. With little additional return being generated over the remaining 60 days. The results for the short portfolio are nowhere near as tractable with there being significant value added generated in the first several days which then reverses itself with significant added value being generated in the last third of the holding period.

Figure 6.1: Cumulative Average Abnormal Returns (CAAR) Generated by Our Existing Strategies (Without Triggers) for Holding Periods up to 60 Days.

The blue line in the graph shows the CAARs for long portfolio where we have above-median PUE and aggregate positive emotions start in the bottom quartile (at 4pm t-1) and they increase over time. The red line is the CAAR for the short portfolio where we have above-median NUE, and aggregate negative emotions start in the bottom quartile (at 4pm t-1) and they increase over time



There are two implications that we take from this information for how we close out portfolio positions: (i) A holding period of 60 days might be far too long, and (ii) a shorter trigger than 100% may be a better fit for taking advantage of the profits generated over the first few days after the announcement. Therefore, we also evaluated a holding period of 15 days (c.f. 60 days) and a trigger of 25% (c.f. 100%) of the standard deviation of the emotion score. The results for the different combinations of triggers and holding periods are reported in Table 6.3. The results highlight that the performance of the long/short portfolio increases as the holding period and the triggers are reduced. We see that the best of the strategies (with a 15-day holding period and a 25% trigger) returns 60.20%, which is double the annual return on the initial strategy that we examined which has a 60-day holding period and a 100% trigger. This significant increase in performance by reducing the period that stocks are held is consistent with the findings reported in Figure 6.1 which suggest that returns on the proposed strategy peak within less than 20 trading days after the earnings announcement. These results also validate the finding of H. K. Sul et al. (2017) that showed a trading strategy using 10 and 20-day holding periods based on sentiment generated from Twitter can give a positive return of 17.91% and 12.59% respectively. Our strategy of involving both the level and the change in the emotion over the post-announcement period generates a much higher return.

Table 6.3: Results for the Different Combinations of Triggers and Holding Periods

Holding period (Days)	Trigger (%)	Long (%pa)	Short (%pa)	Weighted Long/Short (%pa)
60	100	30.85	5.10	29.60
	25	49.41	30.42	47.63
15	100	50.81	32.31	48.75
	25	62.95	53.64	60.20

Please see the annotation of table 6.1 and 6.2 for trigger and the returns on long and short portfolio. Following Peterson (2015) we calculate the weighted returns on the Long and the Short portfolios to calculate our return on the long/short portfolio. For every year, first, we calculate the weight of our long portfolio (Eq. 14) and our short portfolio (Eq. 15). Then we simply multiply them to get the return on the long/short portfolio (Eq. 16). By decomposing the long/short returns, we can identify the contribution of both the long and short portfolios in the overall returns.

Calculating Weights for Long = Value of Long / (Value of Long + Value of Short) … (Eq. 14)

Calculating Weights for Short = Value of Short / (Value of Long + Value of Short) … (Eq. 15)

Long/short return = (Weight of Long * Return of Long) + (Weight of Short * Return of Short) … (Eq. 16)

We report in Table 6.4 several other characteristics of the four long/short portfolios discussed above. The information confirms that these are aggressive portfolios, but then one would not expect otherwise given the magnitude of the returns being generated. We see that the volatility of the returns on the long portfolio does increase as the holding period is shortened but the increasing Sharpe ratios suggests that this increased volatility is not sufficient to offset the benefits from the higher returns. The story is slightly different when it comes to the short portfolio where the performance improves (i.e., becomes more negative) as the volatility is largely unaffected as the holding period and trigger is reduced, and this is reflected by the increasing Sharpe ratios.

An unsurprising feature of both the long and short portfolios is that they are highly concentrated. Indeed, the best performing of the portfolios holds on average 3.4 stocks in the long portfolio and 1.7 stocks in the short portfolio. This suggests that it is not a strategy in which to invest a large portion of one's wealth, both for risk and liquidity reasons. However, the magnitude of the returns suggests that a relatively minor investment can have significant wealth implications. A $1,000 investment in the best strategy would accumulate over $1.2M. over the 15 years from 2003 to 2017.

The average holding period for the best performing of the strategies (a holding period of 15 days and a trigger of 25%) is seven days for both the long and short portfolio. This is consistent with the evidence presented in Figure 6.1 which suggests that the daily added value of the strategy will peak around five to seven days. The information provided on the unexpected earnings (UE) confirms that we are dealing with the more extreme versions of earnings surprise. Finally, the difference between the average emotions scores at the time of the investment (E_0) and that at the time of reversing the position (E_n) indicates that we have been successful in including stocks which experience a relatively large subsequent movement in emotions.

Table 6.4 Statistics for the Different Combinations of Triggers and Holding Periods

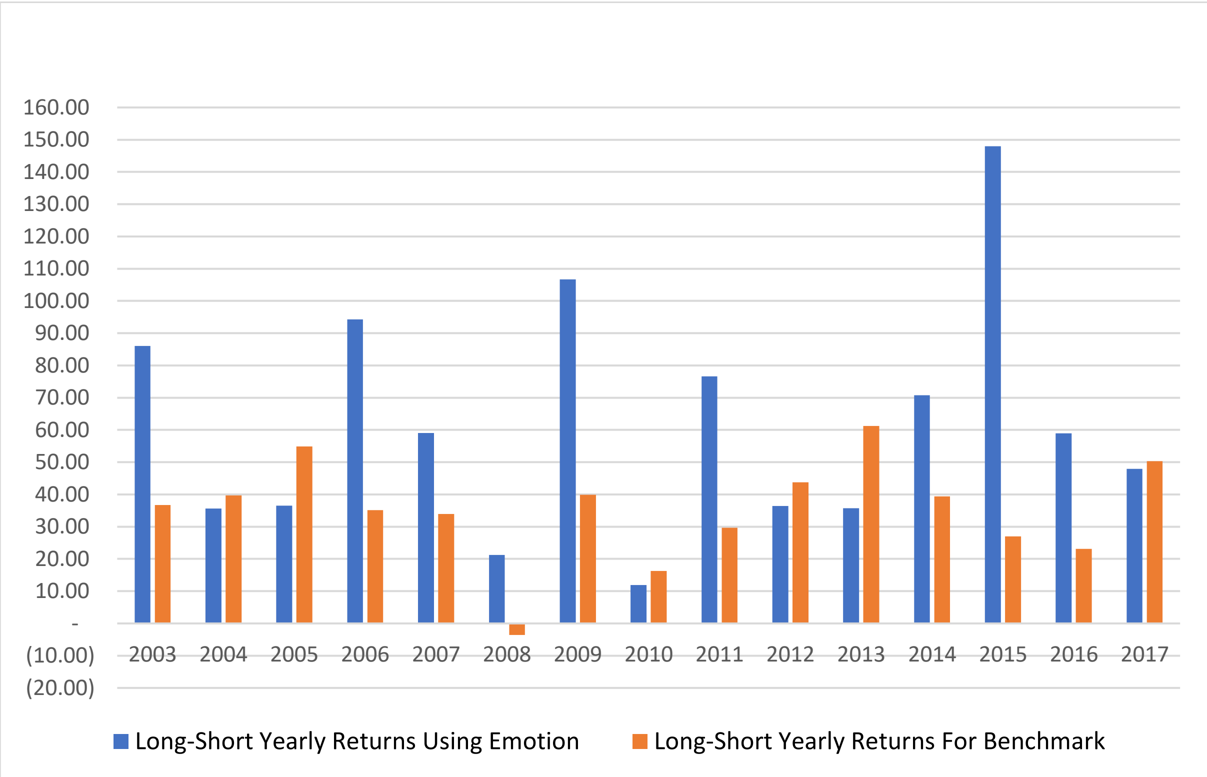
	Holding Period: 60 Days				Holding Period: 15 Days			
	Trigger 100%		Trigger 25%		Trigger 100%		Trigger 25%	
	Long	Short	Long	Short	Long	Short	Long	Short
Return	30.85	5.10	49.41	30.42	50.81	32.31	62.95	53.64
S.D.	0.211	0.100	0.302	0.113	0.296	0.088	0.323	0.103
Sharpe	1.24	0.257	1.351	0.792	1.427	1.006	1.539	1.304
Ave. Stocks	14.07	6.09	4.75	1.85	6.75	7.73	3.36	1.66
Ave. Days Stock held	30	33	10	10	14	15	7	7
Days with no stocks	1	37	197	1012	244	372	739	1082
UE	0.280	-0.651	0.280	-0.651	0.281	-0.651	.0281	-0.651
E_0	0.002	0.012	0.002	0.012	0.002	0.012	0.002	0.012
E_n	0.090	0.077	0.050	0.044	0.056	0.052	0.041	0.039

For the calculation of returns, please see the annotation of table 6.1 & 6.2.

One might assume that a strategy generating such exceptional returns would generate wildly volatile returns over our 15-year sample period. In Figure 6.2, we report the weighted annual returns for the best of the long/short portfolios for each of the 15 years for the long/short portfolio and compare this to the weighted annual return for the benchmark which simply purchases stock on the earnings signal and sells them at the end of the holding period. Hence, the benchmark strategy incorporates no information from the emotion signals and so the difference between the two returns reflects any value-added/subtracted due to incorporating information on emotions into the strategy.

Perhaps the most important insight provided by Figure 6.2 is that our strategy incorporating emotions did not produce a negative return in any of the 15 calendar years covered in our analysis, and this includes the several years that incorporate the Global Financial Crisis. The strategy outperforms the benchmark in nine of the 15 years with the extent of this annual outperformance ranging between an absolute 25% and 125%. In contrast, the outperformance of the benchmark in three of the other six years is by less than 5%.

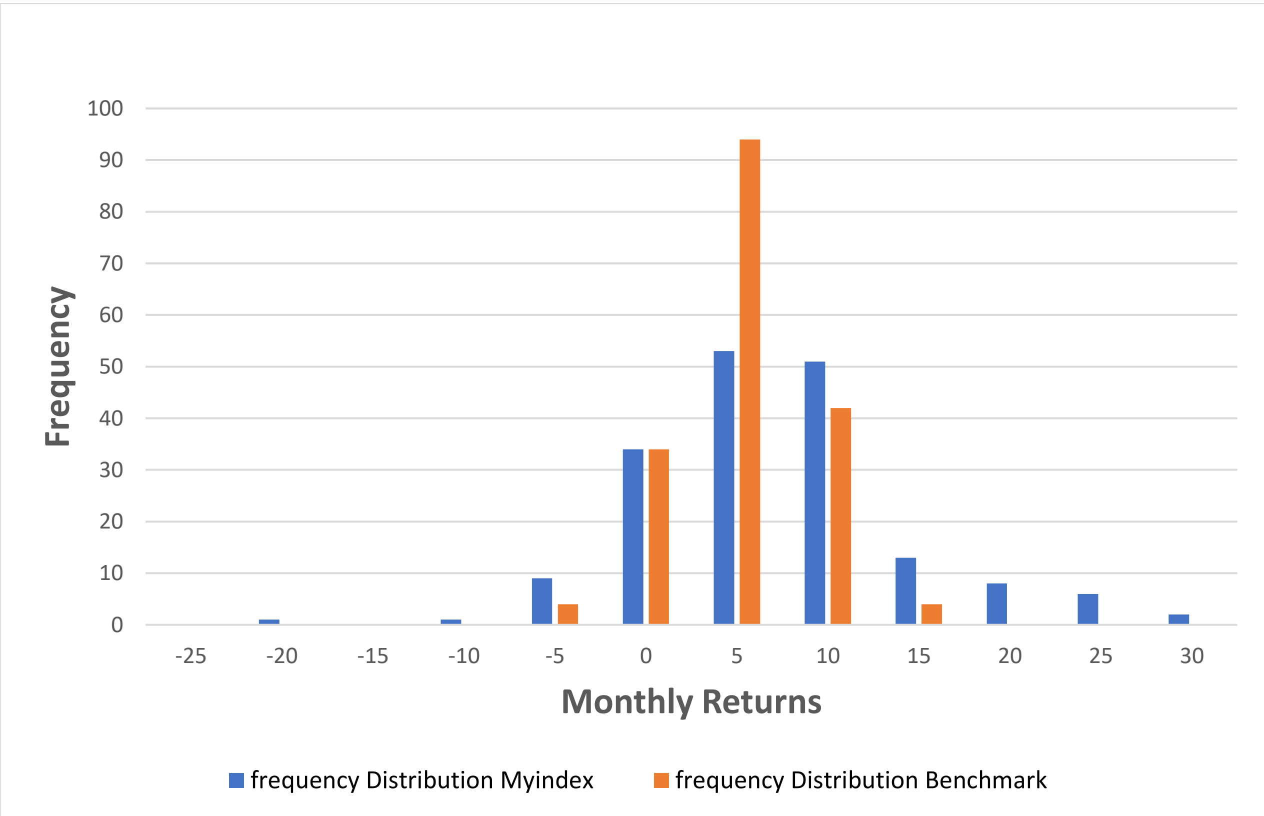
Figure 6.2: Annual Long-Short Return Comparison Between the Emotions Strategy and Benchmark Strategy for T15 @ 25% Trigger



The blue bars in the figure show the annualised returns on a long/short portfolio of strategy where the investment period is 15days and trigger is 25% of the standard deviation. The orange bars in the figure show the annualised returns on the long/short portfolio of the benchmark.

To shed more light on the relative performance of the strategy and the benchmark, in Figure 6.3 we present the frequency distribution of the monthly returns for each strategy. We see that the monthly returns of the benchmark lie in the range from -%5 to +15% whereas there are 10 months during which the returns of the strategy incorporating emotions lies outside this range, with eight of these 10 departures being on the upside. This reflects that while the benchmark distribution is approximately normal (skewness=0.0152), the strategy incorporating emotions has the desirable property of being positively skewed (skewness=0.4469).

Figure 6.3: Long-Short Monthly Return Frequency Distribution for Emotions Strategy for T15 @ 25% Trigger and Benchmark.



The above figure shows the monthly frequency distribution of returns on a long/short portfolio on both the benchmark which does not include any information on the emotions and the strategy where the trigger for trading is 25% of the standard deviation of the emotions. The monthly returns are from 2003 to 2017.

6.5 Cost and Turnover

With daily rebalancing back to equal weights and the average holding period for the strategy being around a week (for the most profitable strategy), it is obvious that the proposed strategy will have a very high turnover. Indeed, we find that the two-way annual turnover of the strategy with a 15-day holding period and a 25% trigger to be 971%. In the first two rows on Table 6.5 we report the turnover for both strategy and the benchmark (which does not incorporate emotions into either the buy or sell decisions), the net returns for several levels of two-way transact costs, and the two-way transactions costs that would reduce return on the strategy and the benchmark to zero (net return = 0%). The available evidence suggests that two-way transaction costs is less than 1% at which level the incorporation of information on emotions into the strategy is clearly adding a significant value[30]. Indeed, the two-way transaction costs would have to be nearly 7% to totally negate any added value from incorporating emotions into our investment strategy.

[30] Tetlock et al. (2008) and H. K. Sul et al. (2017) used a round-trip cost of 10 basis points (bps), whereas in a more recent study, Detzel & Strauss (2018) studied the one-way transaction cost of NYSE, AMEX and NASDAQ stocks and suggested that the industry one-way transaction costs range from 20 to 69 basis points with an average of 35 basis points. We are taking a conservative approach and are using a higher-than-average transaction cost of 50bps as one-way cost.

Table 6.5: Turnover and the Net Returns under Different Levels of transactions Costs: Daily Rebalancing and No Rebalancing

Weighted Long-Short portfolios	Turnover (%pa)	Two-way Cost @ % of Turnover				Net return = 0 %
		0%	0.50%	1.00%	1.50%	
Strategy Return for T15 @25% (%pa) with Daily Rebalancing	971	60.2	55.35	50.49	45.64	6.2
Benchmark Return for T15 (%pa) with Daily Rebalancing	530	35.61	32.96	30.31	27.67	6.7
Strategy Return for T15 @25% (%pa) with No Rebalancing	768	50.81	46.97	43.13	39.29	6.6
Benchmark Return for T15 (%pa) with No Rebalancing	443	28.16	25.95	23.73	21.52	6.4

For calculation of long/short returns, please see annotation of table 6.3. For calculation of Turnover, please see the Appendix 1.

Undoubtedly, we have identified a high return/high turnover strategy, but the question is whether the net returns can be further increased by amending the rebalancing strategy with the objective of reducing the level of turnover. To reduce the turnover, we implemented a strategy where the holdings were not rebalanced at the end of each day but rather the stock purchases and sales are used as best as possible to maintain equal weights within the long and short portfolios[31]. The performance and turnover using this new approach to rebalancing are reported in third and fourth rows of Table 6.5. We can see from the information provided that the amended rebalancing strategy resulted in a reduction in the level of turnover by just over 20%, and so a proportional reduction in indicative transaction costs. However, we find that any savings in transactions costs are more than offset by a reduction in gross returns of in excess of 9% p.a. As a consequence, the change in the rebalancing strategy has had the

[31] Please see the Appendix2 for details on our trading strategy with minimum rebalancing.

desired impact on transaction costs but has resulted in annual net returns declining by about 7.5%. Hence, over our sample period, it would have been preferable to stick with daily rebalancing to equal weights rather than to pursue the alternative that we investigated[32].

The end conclusion that we draw from our analysis is that incorporating emotions into the investment strategy certainly does result in higher turnover and transaction costs, but these are far outweighed by the very high returns realised by exploiting the mispricing opportunities generated by emotions.

6.6 Emotions and Factors

There is ample evidence of the existence of several factors, exposure to which will generate excess returns (Ali et al., 2003; Detzel & Strauss, 2018). Many would argue that exposure to these factors is something like a free lunch and so the performance of any strategy is best measured by the returns that it generates over and above that attributable to these various factors. In this section of the chapter, we report this added performance in the context of the one factor model (CAPM), and the Fama-French three-factor and five-factor models (Fama & French, 1993, 2015). The results for our four strategies are reported in Table 6.6.

The two strategies with the shorter time horizons (T15) that generate the greater added value both only display exposure to the market factor and generates an alpha in the range of 1.3% to 1.4% per month which is equivalent to an annualized return of around 18%. The two strategies with the longer holding period (T60) which generate slightly lower added value display exposure not only to the market but also to growth and the more conservative stocks. The T60 strategy combined with a 100% trigger returned an annualised alpha of approximately 12% while that combined with a 25% trigger returned an annualised alpha of

[32] This does not deny that there may not be more optimal rebalancing strategies to both those investigated, both now and in the future.

just less than 10%. The fact that the alphas for all four strategies are highly significant confirms the added value for building an investment strategy around human emotion scores.

Table 6.6: Results from applying 1-factor, 3-factor, and 5-factor models to monthly returns of weighted long/short portfolio for each of four strategies

	T15@25%			T15@100%			T60@25%			T60@100%		
Vars.	1-Factor	3-Factor	5-Factor	1-Factor	3-Factor	5-Factor	1-Factor	3-Factor	5-Factor	1-Factor	3-Factor	5-Factor
Alpha	0.0136***	0.0137***	0.0130***	0.0139***	0.0140***	0.0129***	0.00788***	0.00777***	0.00739***	0.00993***	0.00978***	0.00948***
Market	0.0949*	0.119**	0.155**	0.261***	0.233***	0.286***	0.182***	0.203***	0.226***	0.297***	0.310***	0.338***
SMB		-0.136	-0.118		-0.0113	0.0381		-4.58e-06	-0.00667		0.0659	0.0118
HML		0.0342	-0.0104		0.177	0.149		-0.120**	-0.179**		-0.155*	-0.248***
RMW			0.148			0.295			0.0614			0.0194
CMA			0.202			0.109			0.205*			0.348**
R-Sq.	0.020	0.032	0.045	0.075	0.087	0.100	0.128	0.148	0.165	0.172	0.191	0.210

To test the added performance of our strategy, we run regressions of our long/short monthly return against 1-Factor (CAPM), Fama and French 3-Factor (FF3), and Fama and French 5-Factor (FF5) models. The monthly data on the factors is downloaded from the Fama and French's website. We run the following regressions:

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \varepsilon \text{ ... (Eq. 6.1)}$$

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon \text{ ... (Eq. 6.2)}$$

$$R_{it} - R_{ft} = \alpha + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \varepsilon \text{ ... (Eq. 6.3)}$$

R_{it} is the monthly return on a long/short portfolio "i" at time "t". R_{ft} is the monthly risk-free rate. MktRF (Market), SMB, HML, RMW and CMA are the proposed factors by (Fama & French, 1993, 2015). *** p<0.01, ** p<0.05, * p<0.1

6.6 Can We Do Better?

The best strategy that we have identified delivered a net return of 50.49% resulting in a $1000 investment accumulating to almost $460,000 over 15 years. However, we have previously indicated that there are six moving parts to the strategy, and we have chosen to only investigate variations in three of them (the trigger, the holding period, and the rebalancing strategy). The other three variables are (i) the definition that we use for positive and negative emotions (we are using just the simple average of the individual positive and negative emotions), (ii) the definition that we are using for low emotions (we have used the bottom quartile), and (iii) the definition that we are using for high good and bad news (we are using the top 50%). There are other combinations of these variables in the process which will yield annualised net returns in excess of 60% and so would grow our $1000 investment to in excess of $1M over the 15 years.

Before closing, we would like to say something about the possible accusation that our findings are heavily data-mined. We would argue against this, based on the defence that the strategy directly flows from our previous findings as to how emotions influence stock valuation at, and after the release of, earnings news. Further, and most importantly, the findings in the previous papers are quite intuitive and so confirm what one might reasonably expect. The success of the strategy going forward will largely depend on whether the results for the S&P 500 stocks over the 15-year period are representative of how emotions fundamentally impact on prices.

6.7 Some Concluding Comments

The focus of this paper has been on demonstrating how information about human emotions can be used to devise a profitable investment strategy. Based on the insights provided in the two previous chapters, we incorporated emotions into a strategy where they influence the timing of both purchasing/short selling stocks and for reversing these transactions. Our basic strategy for the long portfolio is to acquire stocks shortly after companies release exceedingly good earnings news at a time when positive emotions relating to the company are low, and to reverse this transaction either when the positive emotions increase by a pre-specified amount or at the end of the holding period (whichever comes first). Equally, this strategy would also involve selling short stocks in shortly after they release exceedingly bad earnings news at a time when negative emotions relating to the company are low, and to reverse this transaction either when the negative emotions increase by a pre-specified amount or at the end of the holding period (whichever comes first). The rationale is that the prevailing emotions cause an underreaction to the earnings news which is corrected if there is a subsequent upwards movement in the emotions. Our analysis found that the performance improved as one shortened the holding period and set a more sensitive trigger for determining the reversal of the transaction. This finding is consistent with any peaks and troughs in emotions being short-lived.

Our findings provide evidence to suggest that the emotions as expressed in postings in the news and social media are absorbed by individuals and impact on their investment decisions. They further suggest that any resulting distortions in pricings only correct if there is a subsequent change in emotions. Indeed, we would suggest that the price of a stock at any point in time, and how it moves over time, is very much conditioned by the existing environment which is not only affected by investor emotions relating to stocks, but other factors, such as market uncertainty and market sentiment. Any investment strategy which could capture all three is likely to realise exceptional returns, but the evaluation of such a complex strategy will have to wait for another day.

Chapter 7: Conclusion

This thesis examines the impact of emotions engendered by the news and social media on decision-making by investors. The thesis consists of three empirical studies that focus on different research questions. The first empirical chapter investigates the relationship between investor emotions and their decision-making at the time of the release of new company information. The second empirical chapter extends the investigation to subsequent 60 trading days of earnings announcements. Finally, in the third empirical chapter, we investigate if we can use the insights from the first two empirical chapters to develop an investment strategy to exploit possible mispricing opportunities suggested by the analysis in the previous two papers.

We study the companies listed on the S&P 500 and use data on 10 different emotions obtained from a proprietary dataset of the Thomson Reuters MarketPsych Index from 1998 to 2017. This data set is calculated based on a set textual analysis of numerous sources from both the formal news media and social media.

7.1 Key Findings from Empirical Chapters

Chapter 4: The primary focus of this paper is on how the emotions generated by postings on the news and social media impact the behaviour of investors and, by implication, the pricing of financial assets. The proposition is that the emotions generated by the media sources will have both a direct and indirect impact on how investors value stocks. The data that we use to test this proposition comprises four positive, five negative, and one neutral emotion indices extracted from a textual analysis of social and news media postings. For example, the analysis of the news and social media content might suggest that the postings are very gloomy about the prospects of a particular firm. Our concern is whether this emotion of gloom is absorbed by investors, affects their decision-making, and thus impacts prices. We investigate this by measuring whether there is a relationship between the emotions engendered in the media and how stocks are priced around the time of an earnings announcement. We demonstrate that measures of emotions generated by the news and social media emotion measures are not only influential in shaping share prices directly, but they have the potential to impact valuation indirectly by affecting the sensitivity of the investors' response to new earnings information.

Chapter 5: The important takeaway from the previous chapter is that there is a potential underreaction to good news when it is released at a time when positive(negative) emotions are low(high) and vice versa for bad news. In this study, we examine the impact of emotions on stock prices over the post-announcement period which has been identified in numerous studies as a period when stock valuations continue to drift, otherwise known as the post-earnings announcement drift (PEAD). We are particularly interested in the role played by the level of emotions at the time of the announcement, and the path taken by emotions during the post-announcement period, in explaining the existence of PEAD. Our results show that both the level of emotions and changes in the level of emotions, influence PEAD but, on balance, it is the change in emotions that would appear to play the greater role.

Chapter 6: This chapter focuses on identifying whether it is possible to use available information on human emotions to identify and exploit mispricing in equity pricing. We draw on several key insights from the previous two chapters to formulate our investment strategy. Our results from chapter 4 suggest possible underpricing of stocks due to the prevailing emotions at the time of an earnings release. Our findings in chapter 5 suggest that the magnitude of PEAD is very much dependent on the path taken by emotions over the post-announcement period. Based on the insights from these two chapters, we create a basic investment strategy that involves acquiring (selling) shortly after companies release exceedingly good (bad) earnings news at a time when positive (negative) emotions relating to the company are low. We then reverse this transaction either (i) when the positive (negative) emotions increase by a pre-specified amount or (ii) at the end of the prescribed holding period (whichever comes first). The rationale behind the strategy is that the prevailing emotions cause an underreaction to the earnings news, which is corrected if there is a subsequent upward movement in the emotions. We found that this strategy produced high abnormal returns even after considering transaction costs. These findings, along with those from the previous two chapters, confirm that emotions have a very real, and continuing, impact on stock valuations.

7.2 Future Research

This thesis focuses on the impact of emotions on investor decision-making in the S&P 500 from 1998 to 2017. In the empirical chapters, we have validated the importance of the role of emotions in explaining mispricing and how profitable investment strategies can be developed by exploiting this knowledge. Our investigations open the prospect for various lines of future research. Potential future research could explore the investment strategies that are generated using high-frequency financial data of companies. As under-reaction to earnings announcements is a global phenomenon and is not limited to the U.S. financial markets, another line of research could focus on the impact of emotions in other international markets. This will enable investors to compare the different investment strategies and select the ones that have the highest potential. Third, we have only considered stocks in our analysis. Future research on the impact of emotions on other assets, such as the crypto market, would also yield some interesting findings.

References

Agrawal, N. & Duhachek, A. (2010). Emotional compatibility and the effectiveness of antidrinking messages: A defensive processing perspective on shame and guilt. *Journal of Marketing Research*, *47*(2), 263–273. SAGE Publications Sage CA: Los Angeles, CA.

Agrawal, N., Han, D. & Duhachek, A. (2013). Emotional agency appraisals influence responses to preference inconsistent information. *Organizational Behavior and Human Decision Processes*, *120*(1), 87–97. Elsevier.

Ali, A., Hwang, L.-S. & Trombley, M. A. (2003). Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics*, *69*(2), 355–373. Elsevier.

Almaskati, N., Bird, R., Lu, Y. & Yeung, D. (2019). Corporate Governance, Information Uncertainty and Market Reaction to Information Signals. *Working Paper*.

An, N., Wang, B., Pan, P., Guo, K. & Sun, Y. (2018). Study on the influence mechanism of air quality on stock market yield and Volatility: Empirical test from China based on GARCH model. *Finance Research Letters*, *26*, 119–125. Elsevier.

Andersen, P. A. & Guerrero, L. K. (1996). Principles of communication and emotion in social interaction. *Handbook of communication and emotion* (pp. 49–96). Elsevier.

Andrade, E. B. & Ariely, D. (2009). The enduring impact of transient emotions on decision making. *Organizational Behavior and Human Decision Processes*, *109*(1), 1–8. Elsevier.

Angie, A. D., Connelly, S., Waples, E. P. & Kligyte, V. (2011). The influence of discrete emotions on judgement and decision-making: A meta-analytic review. *Cognition & Emotion*, *25*(8), 1393–1422. Taylor & Francis.

Antweiler, W. & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, *59*(3), 1259–1294. Wiley Online Library.

Audrino, F. & Tetereva, A. (2019). Sentiment spillover effects for US and European companies. *Journal of Banking & Finance*, *106*, 542–567. Elsevier.

Ayers, B. C., Li, O. Z. & Yeung, P. E. (2011). Investor trading and the post-earnings-announcement drift. *The Accounting Review*, *86*(2), 385–416.

Baker, M. & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680. Wiley Online Library.

Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics*, *6*(2-3), 103–126. Elsevier.

Ball, R. & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of accounting research*, 159–178. JSTOR.

Barbalet, J. M. (1999). William James' theory of emotions: Filling in the picture. *Journal for the Theory of Social Behaviour, 29*(3), 251–266. Wiley Online Library.

Barberis, N., Shleifer, A. & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307–343. Elsevier.

Bartlett, M. Y. & DeSteno, D. (2006). Gratitude and prosocial behavior: Helping when it costs you. *Psychological science*, *17*(4), 319–325. SAGE Publications Sage CA: Los Angeles, CA.

Bartov, E., Faurel, L. & Mohanram, P. S. (2017). Can twitter help predict firm-level earnings and stock returns? *The Accounting Review*, *93*(3), 25–57. American Accounting Association.

Bartov, E., Radhakrishnan, S. & Krinsky, I. (2000). Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review*, *75*(1), 43–63.

Battalio, R. H. & Mendenhall, R. R. (2005). Earnings expectations, investor trade size, and anomalous returns around earnings announcements. *Journal of Financial Economics*, *77*(2), 289–319. Elsevier.

Bechara, A. (2004). The role of emotion in decision-making: evidence from neurological patients with orbitofrontal damage. *Brain and cognition*, *55*(1), 30–40. Elsevier.

Bechara, A., Damasio, H., Tranel, D. & Damasio, A. R. (1997). Deciding advantageously before knowing the advantageous strategy. *Science (80-.).*, *275*(5304), 1293–1295. American Association for the Advancement of Science.

Beckers, S. (2018). Do social media trump news? The relative importance of social media and news based sentiment for market timing. *The Journal of Portfolio Management, 45*(2), 58–67. Institutional Investor Journals Umbrella.

Bernard, V. & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting research*, 1–36. JSTOR.

Bhattacharya, N. (2001). Investors' trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review*, *76*(2), 221–244.

Bhushan, R. (1994). An informational efficiency perspective on the post-earnings announcement drift. *Journal of Accounting and Economics*, *18*(1), 45–65. Elsevier.

Bird, R., Choi, D. F. & Yeung, D. (2014). Market uncertainty, market sentiment, and the post-earnings announcement drift. *Review of Quantitative Finance and Accounting*, *43*(1), 45–73. Springer.

Bird, R. & Yeung, D. (2012). How do investors react under uncertainty? *Pacific-Basin Finance Journal*, *20*(2), 310–327. Elsevier.

Biss, R. K. & Hasher, L. (2011). Delighted and distracted: Positive affect increases priming for irrelevant information. *Emotion*, *11*(6), 1474. American Psychological Association.

Blankespoor, E., Miller, G. S. & White, H. D. (2014). The role of dissemination in market liquidity: Evidence from firms' use of Twitter™. *The Accounting Review*, *89*(1), 79–112. American Accounting Association.

Boehmer, E. & Wu, J. (Julie). (2013). Short Selling and the Price Discovery Process. *The Review of Financial Studies*, *26*(2), 287–322.

Bollen, J. & Mao, H. (2011). Twitter mood as a stock market predictor. *Computer (Long. Beach. Calif).*, (10), 91–94. IEEE.

Bollen, J., Mao, H. & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of computational science*, *2*(1), 1–8. Elsevier.

Bormann, S.-K. (2013). *Sentiment indices on financial markets: What do they measure?*

Breaban, A. & Noussair, C. N. (2018). Emotional state and market behavior. *Review of Finance*, *22*(1), 279–309. Oxford University Press.

Brosch, T., Scherer, K. R., Grandjean, D. M. & Sander, D. (2013). The impact of emotion on perception, attention, memory, and decision-making. *Swiss medical weekly*, *143*, w13786.

Calvo, R. A. & Mac Kim, S. (2013). Emotions in text: dimensional and categorical models. *Computational Intelligence*, *29*(3), 527–543. Wiley Online Library.

Camerer, C., Loewenstein, G. & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of economic Literature*, *43*(1), 9–64.

Cao, M. & Wei, J. (2005). Stock market returns: A note on temperature anomaly. *Journal of Banking & Finance*, *29*(6), 1559–1573. Elsevier.

Cao, S. S. & Narayanamoorthy, G. S. (2012). Earnings volatility, post-earnings announcement drift, and trading frictions. *Journal of Accounting Research*, *50*(1), 41–74. Wiley Online Library.

Caplovitz Barrett, K. (2005). The origins of social emotions and self-regulation in toddlerhood: New evidence. *Cognition & Emotion*, *19*(7), 953–979. Taylor & Francis.

Caquard, S. & Griffin, A. (2018). Mapping emotional cartography. *Cartographic Perspectives*, (91), 4–16.

Chae, J. (2005). Trading volume, information asymmetry, and timing information. *The Journal of Finance*, *60*(1), 413–442. Wiley Online Library.

Chan, L. K., Jegadeesh, N. & Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance*, *51*(5), 1681–1713. Wiley Online Library.

Chan, L. K. & Lakonishok, J. (2004). Value and growth investing: Review and update. *Financial Analysts Journal*, 71–86. JSTOR.

Chan, W. S. (2003). Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics*, *70*(2), 223–260. Elsevier.

Chen, H., De, P., Hu, Y. J. & Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, *27*(5), 1367–1403. Oxford University Press.

Chen, J. Z., Lobo, G. J. & Zhang, J. H. (2017). Accounting quality, liquidity risk, and post-earnings-announcement drift. *Contemporary Accounting Research*, *34*(3), 1649–1680. Wiley Online Library.

Chordia, T., Goyal, A., Sadka, G., Sadka, R. & Shivakumar, L. (2009). Liquidity and the post-earnings-announcement drift. *Financial Analysts Journal*, *65*(4), 18–32. CFA Institute.

Chordia, T., Huh, S.-W. & Subrahmanyam, A. (2009). Theory-based illiquidity and asset pricing. *Review of Financial Studies*, *22*(9), 3629–3668. Soc Financial Studies.

De Choudhury, M., Counts, S. & Horvitz, E. (2013). Predicting postpartum changes in emotion and behavior via social media. *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 3267–3276).

Chung, D. Y. & Hrazdil, K. (2011). Market Efficiency and the Post-Earnings Announcement Drift. *Contemporary Accounting Research*, *28*(3), 926–956. Wiley Online Library.

Clore, G. L., Ortony, A. & Foss, M. A. (1987). The psychological foundations of the affective lexicon. *Journal of Personality and Social Psychology*, *53*(4), 751. American Psychological Association.

Clore, G. L., Schwarz, N. & Conway, M. (1994). Affective causes and consequences of social information processing. *Handbook of social cognition*, *1*, 323–417.

Da, Z., Engelberg, J. & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies*, *28*(1), 1–32. Oxford University Press.

Damasio, A. R. (1994). Descartes’ Error. Emotion, Reason and the Human Brain. New York (Grosset/Putnam) 1994.

Das, S. R. & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science, 53*(9), 1375–1388. INFORMS.

Daszyńska-Żygadło, K., Szpulak, A. & Szyszka, A. (2014). Investor sentiment, optimism and excess stock market returns. Evidence from emerging markets. *Business & Economic Horizons, 10*(4).

DeFond, M., Hung, M. & Trezevant, R. (2007). Investor protection and the information content of annual earnings announcements: International evidence. *Journal of Accounting and Economics, 43*(1), 37–67.

Deloitte, T. (2008). *Most consumers read and rely on online reviews; companies must adjust*.

Detzel, A. & Strauss, J. (2018). Combination return forecasts and portfolio allocation with the cross-section of book-to-market ratios. *Review of Finance*, *22*(5), 1949–1973. Oxford University Press.

Dienstbier, R. A. & Munter, P. O. (1971). Cheating as a function of the labeling of natural arousal. *Journal of Personality and Social Psychology*, *17*(2), 208. American Psychological Association.

Dougal, C., Engelberg, J., Garcia, D. & Parsons, C. A. (2012). Journalists and the stock market. *The Review of Financial Studies*, *25*(3), 639–679. Oxford University Press.

Doyle, J. T., Lundholm, R. J. & Soliman, M. T. (2006). The extreme future stock returns following I/B/E/S earnings surprises. *Journal of Accounting Research*, *44*(5), 849–887. Wiley Online Library.

Du, W. (2020). News and Market Efficiency in the Japanese Stock Market. *Journal of Behavioral Finance*, 1–14. Taylor & Francis.

Duxbury, D., Gärling, T., Gamble, A. & Klass, V. (2020). How emotions influence behavior in financial markets: a conceptual analysis and emotion-based account of buy-sell preferences. *The European Journal of Finance*, *26*(14), 1417–1438. Taylor & Francis.

Edmans, A., Garcia, D. & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, *62*(4), 1967–1998. Wiley Online Library.

Elster, J. (1998). Emotions and economic theory. *Journal of economic literature*, *36*(1), 47–74. JSTOR.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*(3), 283–306. Elsevier.

Fama, E. F. & French, K. R. (1993). Common risk factors in stock and bond returns. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. Elsevier.

Fama, & French, K. (1992). The cross-section of expected stock returns. *Journal of Finance*, *47*(2), 427–465.

Fehr, E. & Gächter, S. (2002). Altruistic punishment in humans. *Nature*, *415*(6868), 137–140. Nature Publishing Group.

Fenton-O'Creevy, M., Soane, E., Nicholson, N. & Willman, P. (2011). Thinking, feeling and deciding: The influence of emotions on the decision making and performance of traders. *Journal of Organizational Behavior*, *32*(8), 1044–1061. Wiley Online Library.

Finter, P., Niessen-Ruenzi, A. & Ruenzi, S. (2012). The impact of investor sentiment on the German stock market. *Zeitschrift für Betriebswirtschaft*, *82*(2), 133–163. Springer.

Fisher, K. L. & Statman, M. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management*, *30*(1), 115–127. Institutional Investor Journals Umbrella.

Frieder, L. & Subrahmanyam, A. (2004). Nonsecular regularities in returns and volume. *Financial Analysts Journal*, *60*(4), 29–34. Taylor & Francis.

Frijda, N. H. (1986). *The emotions*. Cambridge University Press.

Gao, G. & Hitt, L. M. (2012). Information technology and trademarks: Implications for product variety. *Management Science, 58*(6), 1211–1226. INFORMS.

Garcia, D. (2013). Sentiment during recessions. *The Journal of Finance*, *68*(3), 1267–1300. Wiley Online Library.

Garg, N. (2004). *The role of affect in judgment and decision making*.

Gasper, K. & Clore, G. L. (2002). Attending to the big picture: Mood and global versus local processing of visual information. *Psychological science*, *13*(1), 34–40. SAGE Publications Sage CA: Los Angeles, CA.

Ghosh, D. & Vogt, A. (2012). Outliers: An evaluation of methodologies. *Joint statistical meetings* (Vol. 2012).

Goldenberg, A., Garcia, D., Halperin, E. & Gross, J. J. (2020). Collective emotions. *Current Directions in Psychological Science*, *29*(2), 154–160. Sage Publications Sage CA: Los Angeles, CA.

Gormley, T. A. & Matsa, D. A. (2014). Common errors: How to (and not to) control for unobserved heterogeneity. *The Review of Financial Studies*, *27*(2), 617–661. Oxford University Press.

Greenwood, R. & Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, *27*(3), 714–746. Oxford University Press.

Griffith, J., Najand, M. & Shen, J. (2019). Emotions in the Stock Market. *Journal of Behavioral Finance*, 1–15. Taylor & Francis.

Grinold, R. C. & Kahn, R. N. (2000). The Efficiency Gains of Long-Short Investing. *Financial Analysts Journal*, *56*(6), 40–53. Taylor & Francis.

Guo, K., Sun, Y. & Qian, X. (2017). Can investor sentiment be used to predict the stock price? Dynamic analysis based on China stock market. *Physica A: Statistical Mechanics and its Applications*, *469*, 390–396. Elsevier.

Hemenover, S. & Zhang, S. (2004). Anger, personality, and optimistic stress appraisals. *Cognition and Emotion*, *18*(3), 363–382. Taylor & Francis.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., et al. (2005). “Economic man” in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. *Behavioral and brain sciences*, *28*(6), 795–815. Cambridge

University Press.

Heston, S. L. & Sinha, N. R. (2017). News vs. sentiment: Predicting stock returns from news stories. *Financial Analysts Journal*, *73*(3), 67–83. Taylor & Francis.

Hirshleifer, D. A., Myers, J. N., Myers, L. A. & Teoh, S. H. (2008). Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades. *The Accounting Review*, *83*(6), 1521–1550.

Hirshleifer, D., Lim, S. S. & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289–2325. Wiley Online Library.

Hirshleifer, D. & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance*, *58*(3), 1009–1032. Wiley Online Library.

Hung, M., Li, X. & Wang, S. (2014). Post-earnings-announcement drift in global markets: Evidence from an information shock. *The Review of Financial Studies*, *28*(4), 1242–1283. Oxford University Press.

Isen, A. M., Daubman, K. A. & Nowicki, G. P. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology*, *52*(6), 1122. American Psychological Association.

Jacobsen, B. & Marquering, W. (2008). Is it the weather? *Journal of Banking & Finance*, *32*(4), 526–540. Elsevier.

Kaestner, M. (2006). Investors' misreaction to unexpected earnings: Evidence of simultaneous overreaction and underreaction. *Available at SSRN 868346*.

Kamstra, M. J., Kramer, L. A. & Levi, M. D. (2003). Winter Blues: A SAD Stock Market Cycle. *American Economic Review*, *93*(1), 324–343.

Kaplanski, G. & Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, *95*(2), 174–201.

Karagozoglu, A. K. & Fabozzi, F. J. (2017). Volatility Wisdom of Social Media Crowds. *The Journal of Portfolio Management*, *43*(2), 136–151. Institutional Investor Journals Umbrella.

Karampatsas, N., Malekpour, S. & Mason, A. (2018). Beyond Market Mood: Firm Sentiment and the Response to Corporate Earnings Announcements. *Available on SSRN*.

Kaufman, B. E. (1999). Emotional arousal as a source of bounded rationality. *Journal of Economic Behavior & Organization*, *38*(2), 135–144. Elsevier.

Kausar, A., Taffler, R. J. & Tan, C. (2009). The going-concern market anomaly. *Journal of Accounting Research*, *47*(1), 213–239. Wiley Online Library.

Ke, B. & Ramalingegowda, S. (2005). Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics*, *39*(1), 25–53. Elsevier.

Keltner, D. & Lerner, J. S. (2010). Emotion. John Wiley & Sons, Inc.

Kemper, T. D. (1978). Toward a sociology of emotions: Some problems and some solutions. *The American Sociologist*, 30–41. JSTOR.

Kijkasiwat, P. (2021). Journal of Behavioral and Experimental Finance.

Kim, H., Park, K. & Schwarz, N. (2010). Will this trip really be exciting? The role of incidental emotions in product evaluation. *Journal of Consumer Research*, *36*(6), 983–991. The University of Chicago Press.

Kim, K., Pandit, S. & Wasley, C. E. (2016). Macroeconomic uncertainty and management earnings forecasts. *Accounting Horizons*, *30*(1), 157–172. American Accounting Association.

Kleinginna, P. R. & Kleinginna, A. M. (1981). A categorized list of emotion definitions, with suggestions for a consensual definition. *Motivation and emotion*, *5*(4), 345–379. Springer.

Kothari, S. (2001). Capital markets research in accounting. *Journal of accounting and economics*, *31*(1), 105–231. Elsevier.

Kumar, A., Ekbal, A., Kawahra, D. & Kurohashi, S. (2019). Emotion helps sentiment: A multi-task model for sentiment and emotion analysis. *2019 International Joint Conference on Neural Networks (IJCNN)* (pp. 1–8).

Leinweber, D. & Sisk, J. (2011). Event-driven trading and the “new news.” *The Journal of Portfolio Management*, *38*(1), 110–124. Institutional Investor Journals Umbrella.

Lemmon, M. & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies*, *19*(4), 1499–1529. Soc Financial Studies.

Lench, H. C., Flores, S. A. & Bench, S. W. (2011). Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: a meta-analysis of experimental emotion elicitations. *Psychological bulletin*, *137*(5), 834. American Psychological Association.

Lerner, J. S. & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology*, *81*(1), 146. American Psychological Association.

Lerner, J. S., Li, Y., Valdesolo, P. & Kassam, K. S. (2015). Emotion and decision making. *Annual review of psychology*, *66*.

Lerner, J. S., Li, Y. & Weber, E. U. (2013). The financial costs of sadness. *Psychological science*, *24*(1), 72–79. Sage Publications Sage CA: Los Angeles, CA.

Lerner, J. S. & Tiedens, L. Z. (2006). Portrait of the angry decision maker: How appraisal tendencies shape anger’s influence on cognition. *Journal of behavioral decision making*, *19*(2), 115–137. Wiley Online Library.

Leszczensky, L. & Wolbring, T. (2019). How to deal with reverse causality using panel data? Recommendations for researchers based on a simulation study. *Sociological Methods & Research*, 0049124119882473. SAGE Publications Sage CA: Los Angeles, CA.

Liu, B., Govindan, R. & Uzzi, B. (2016). Do emotions expressed online correlate with actual changes in decision-making?: The case of stock day traders. *PLoS One*, *11*(1), e0144945. Public Library of Science San Francisco, CA USA.

Livnat, J. & Mendenhall, R. R. (2006). Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of accounting research*, *44*(1), 177–205. Wiley Online Library.

Livnat, J. & Petrovits, C. (2019). Investor Sentiment, Post-Earnings Announcement Drift, and Accruals. *The Journal of Applied Business and Economics*, *21*(8), 67–80. North American Business Press.

Loewenstein, G. (2000). Emotions in economic theory and economic behavior. *American economic review*, *90*(2), 426–432.

De Long, J. B., Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of political Economy*, *98*(4), 703–738. The University of Chicago Press.

Loughran, T. & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65. Wiley Online Library.

Loughran, T. & McDonald, B. (2013). IPO first-day returns, offer price revisions, volatility, and form S-1 language. *Journal of Financial Economics*, *109*(2), 307–326. Elsevier.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13–39. JSTOR.

Maheswaran, D. & Chen, C. Y. (2006). Nation equity: incidental emotions in country-of-origin effects. *Journal of consumer research*, *33*(3), 370–376. The University of Chicago Press.

McQueen, G. & Roley, V. V. (1993). Stock prices, news, and business conditions. *The review of financial studies*, *6*(3), 683–707. Oxford University Press.

De Mello, G., MacInnis, D. J. & Stewart, D. W. (2007). Threats to hope: effects on reasoning about product information. *Journal of Consumer Research*, *34*(2), 153–161. The University of Chicago Press.

Mendenhall, R. R. (2004). Arbitrage Risk and Post-Earnings-Announcement Drift. *The Journal of Business*, *77*(4), 875–894. University of Chicago Press.

Mian, G. M. & Sankaraguruswamy, S. (2012). Investor sentiment and stock market response to earnings news. *The Accounting Review*, *87*(4), 1357–1384. American Accounting Association.

Michaelides, A., Milidonis, A. & Nishiotis, G. P. (2019). Private information in currency markets. *Journal of Financial Economics*, *131*(3), 643–665. Elsevier.

Michaelides, A., Milidonis, A., Nishiotis, G. P. & Papakyriakou, P. (2015). The adverse effects of systematic leakage ahead of official sovereign debt rating announcements. *Journal of Financial Economics*, *116*(3), 526–547. Elsevier.

Milian, J. A. (2015). Unsophisticated arbitrageurs and market efficiency: overreacting to a history of underreaction? *Journal of Accounting Research*, *53*(1), 175–220. Wiley Online Library.

Miller, G. A. (2003). The cognitive revolution: a historical perspective. *Trends in cognitive sciences*, *7*(3), 141–144. Elsevier.

Mitchell, M., Pulvino, T. & Stafford, E. (2004). Price pressure around mergers. *The Journal of Finance*, *59*(1), 31–63. Wiley Online Library.

Munezero, M., Montero, C. S., Sutinen, E. & Pajunen, J. (2014). Are they different? Affect, feeling, emotion, sentiment, and opinion detection in text. *IEEE transactions on affective computing*, *5*(2), 101–111. IEEE.

Neal, R. & Wheatley, S. M. (1998). Do measures of investor sentiment predict returns? *Journal of Financial and Quantitative Analysis*, *33*(4), 523–547. Cambridge University Press.

Ng, J., Rusticus, T. O. & Verdi, R. S. (2008). Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research*, *46*(3), 661–696. Wiley Online Library.

Nold, C. (2009). Emotional cartography: Technologies of the self. Space Studios.

Nooijen, S. J. & Broda, S. A. (2016). Predicting equity markets with digital online media sentiment: evidence from Markov-switching models. *Journal of Behavioral Finance*, *17*(4), 321–335. Taylor & Francis.

Oh, C. & Sheng, O. (2011). Investigating predictive power of stock micro blog sentiment in forecasting future stock price directional movement.

Oh, O., Agrawal, M. & Rao, H. R. (2013). Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS quarterly*, 407–426. JSTOR.

Oliver, R. L. (1993). Cognitive, affective, and attribute bases of the satisfaction response. *Journal of consumer research*, *20*(3), 418–430. The University of Chicago Press.

Pellert, M., Lasser, J., Metzler, H. & Garcia, D. (2020). Dashboard of sentiment in Austrian social media during COVID-19. *Frontiers in big Data*, *3*, 32. Frontiers Media SA.

Peress, J. (2014). The media and the diffusion of information in financial markets: Evidence from newspaper strikes. *The Journal of Finance, 69*(5), 2007–2043. Wiley Online Library.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of financial studies*, *22*(1), 435–480. Oxford University Press.

Peterson, R. L. (2016). *Trading on sentiment: The power of minds over markets*. John Wiley & Sons.

Pevzner, M., Xie, F. & Xin, X. (2015). When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. *Journal of Financial Economics*, *117*(1), 190–223. Elsevier.

Pham, M. T. (2004). The logic of feeling. *Journal of Consumer Psychology, 14*(4), 360–369. Elsevier.

Pham, M. T. (2007). Emotion and rationality: A critical review and interpretation of empirical evidence. *Review of general psychology*, *11*(2), 155–178. SAGE Publications Sage CA: Los Angeles, CA.

Phelps, E. A. (2006). Emotion and cognition: insights from studies of the human amygdala. *Annu. Rev. Psychol.*, *57*, 27–53. Annual Reviews.

Pinegar, J. M. (2002). Losing sleep at the market: Comment. *American Economic Review*, *92*(4), 1251–1256.

Plutchik, R. (1980). Emotion. *A psychoevolutionary synthesis*. Harper & Row.

Plutchik, R. (1994). The Psychology and Biology of Emotion. HarperCollins College Publishers. *New York*.

Poshakwale, S. & Theobald, M. (2004). Market capitalisation, cross-correlations, the lead/lag structure and microstructure effects in the Indian stock market. *Journal of International Financial Markets, Institutions and Money*, *14*(4), 385–400. Elsevier.

Qiu, L. & Welch, I. (2004). Investor sentiment measures. National Bureau of Economic Research Cambridge, Mass., USA.

Quigley, B. M. & Tedeschi, J. T. (1996). Mediating effects of blame attributions on feelings of anger. *Personality and Social Psychology Bulletin*, *22*(12), 1280–1288. Sage Publications Sage CA: Thousand Oaks, CA.

Raghunathan, R. & Corfman, K. P. (2004). Sadness as pleasure-seeking prime and anxiety as attentiveness prime: The “different affect-different effect”(DADE) model. *Motivation and Emotion*, *28*(1), 23–41. Springer.

Raghunathan, R., Pham, M. T. & Corfman, K. P. (2006). Informational properties of anxiety and sadness, and displaced coping. *Journal of Consumer Research*, *32*(4), 596–601. The University of Chicago Press.

Resch, B., Summa, A., Sagl, G., Zeile, P. & Exner, J.-P. (2015). Urban emotions—Geo-semantic emotion extraction from technical sensors, human sensors and crowdsourced data. *Progress in location-based services 2014* (pp. 199–212). Springer.

Rimé, B. (2009). Emotion elicits the social sharing of emotion: Theory and empirical review. *Emotion review*, *1*(1), 60–85. Sage Publications Sage UK: London, England.

Risius, M., Akolk, F. & Beck, R. (2015). Differential emotions and the stock market-the case of company-specific trading.

Roll, R., Schwartz, E. & Subrahmanyam, A. (2009). Options trading activity and firm valuation. *Journal of Financial Economics*, *94*(3), 345–360.

Romani, S., Grappi, S. & Dalli, D. (2012). Emotions that drive consumers away from brands: Measuring negative emotions toward brands and their behavioral effects.

International Journal of Research in marketing, *29*(1), 55–67. Elsevier.

Rowe, G., Hirsh, J. B. & Anderson, A. K. (2007). Positive affect increases the breadth of attentional selection. *Proceedings of the National Academy of Sciences*, *104*(1), 383–388. National Acad Sciences.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161. American Psychological Association.

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological review*, *110*(1), 145. American Psychological Association.

Ryan, K. F. & Giles, D. E. (1999). Testing for unit roots in economic time series with missing observations. *Messy Data* (pp. 203–242). Emerald Group Publishing Limited.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics*, *80*(2), 309–349. Elsevier.

Sailunaz, K. & Alhajj, R. (2019). Emotion and sentiment analysis from Twitter text. *Journal of Computational Science*, *36*, 101003. Elsevier.

Sambrano, D., Masip, J. & Blandón-Gitlin, I. (2021). How emotions affect judgement and decision making in an interrogation scenario. *Legal and Criminological Psychology*, *26*(1), 62–82. Wiley Online Library.

Saunders, E. M. (1993). Stock prices and Wall Street weather. *The American Economic Review*, *83*(5), 1337–1345. JSTOR.

Scherer, K. R. (2005). What are emotions? And how can they be measured? *Social Science Information*, *44*(4), 695–729.

Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance*, *16*(3), 394–408. Elsevier.

Schwarz, N. (2011). Feelings-as-information theory. *Handbook of theories of social psychology*, *1*, 289–308.

Schwarz, N. & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: informative and directive functions of affective states. *Journal of Personality and Social Psychology*, *45*(3), 513. American Psychological Association.

Shu, H.-C. (2010). Investor mood and financial markets. *Journal of Economic Behavior & Organization*, *76*(2), 267–282. Elsevier.

Shumway, T. (2010). Mood. *Behavioral finance: Investors, corporations, and markets*, 671–679. Wiley Online Library.

Sibley, S. E., Wang, Y., Xing, Y. & Zhang, X. (2016). The information content of the sentiment index. *Journal of Banking & Finance*, *62*, 164–179. Elsevier.

Simon, H. (1990). *Reason in human affairs*. Stanford University Press.

Simon, H. A. (1955). A behavioral model of rational choice. *The quarterly journal of economics*, *69*(1), 99–118. MIT Press.

Smailović, J., Grčar, M., Lavrač, N. & Žnidaršič, M. (2014). Stream-based active learning for sentiment analysis in the financial domain. *Inf. Sci. (Ny).*, *285*, 181–203. Elsevier.

Smith, C. A. & Ellsworth, P. C. (1985). Patterns of cognitive appraisal in emotion. *Journal of Personality and Social Psychology*, *48*(4), 813. American Psychological Association.

Smith, C. A. & Lazarus, R. S. (1990). Emotion and adaptation. *Handbook of personality: Theory and research*, 609–637.

Song, Q., Liu, A. & Yang, S. Y. (2017). Stock portfolio selection using learning-to-rank algorithms with news sentiment. *Neurocomputing*, *264*, 20–28. Elsevier.

Sprenger, T. O., Tumasjan, A., Sandner, P. G. & Welpe, I. M. (2014). Tweets and trades: The information content of stock microblogs. *European Financial Management*, *20*(5), 926–957. Wiley Online Library.

Sul, H., Dennis, A. R. & Yuan, L. I. (2014). Trading on twitter: The financial information content of emotion in social media. *2014 47th Hawaii International Conference on System Sciences* (pp. 806–815).

Sul, H. K., Dennis, A. R. & Yuan, L. (2017). Trading on twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, *48*(3), 454–488. Wiley Online Library.

Sun, A., Lachanski, M. & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. *International Review of Financial Analysis*, *48*, 272–281. Elsevier.

Sun, L., Najand, M. & Shen, J. (2016). Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance*, *73*, 147–164. Elsevier.

Sun, Q. (2015). Stock Price Discovery in Earnings Season. *The International Journal of Business and Finance Research*, *9*(5), 1–15.

Taffler, R. J., Lu, J. & Kausar, A. (2004). In denial? Stock market underreaction to going-concern audit report disclosures. *Journal of Accounting and Economics*, *38*, 263–296. Elsevier.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139–1168. Wiley Online Library.

Tetlock, P. C., Saar-Tsechansky, M. & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, *63*(3), 1437–1467. Wiley Online Library.

Tiedens, L. Z. & Linton, S. (2001). Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. *Journal of Personality and Social Psychology*, *81*(6), 973. American Psychological Association.

Tirunillai, S. & Tellis, G. J. (2012). Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science*, *31*(2), 198–215. INFORMS.

Truong, C. & Corrado, C. (2014). Options trading volume and stock price response to earnings announcements. *Review of Accounting Studies*, *19*(1), 161–209. Springer.

Tumarkin, R. & Whitelaw, R. F. (2001). News or noise? Internet postings and stock prices. *Financial Analysts Journal*, *57*(3), 41–51. Taylor & Francis.

Uhl, M. W., Pedersen, M. & Malitius, O. (2015). What's in the news? Using news sentiment momentum for tactical asset allocation. *The Journal of Portfolio Management, 41*(2), 100–112. Institutional Investor Journals Umbrella.

Vamossy, D. F. (2021). Investor emotions and earnings announcements. *Journal of Behavioral and Experimental Finance*, *30*, 100474. Elsevier.

Wang, B., Choi, W. & Siraj, I. (2018). Local investor attention and post-earnings announcement drift. *Review of Quantitative Finance and Accounting*, *51*(1), 219–252. Springer.

Wang, J. Y. & Markellos, R. N. (2018). Is there an Olympic gold medal rush in the stock market? *The European Journal of Finance*, *24*(17), 1631–1648. Taylor & Francis.

Westbrook, R. A. (1987). Product/consumption-based affective responses and postpurchase processes. *Journal of marketing research*, *24*(3), 258–270. SAGE Publications Sage CA: Los Angeles, CA.

Westbrook, R. A. & Oliver, R. L. (1991). The dimensionality of consumption emotion patterns and consumer satisfaction. *Journal of consumer research*, *18*(1), 84–91. The University of Chicago Press.

Williams, C. D. (2015). Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review*, *90*(2), 785–817. American Accounting Association.

Williamson, M. (2002). Emotions, reason and behaviour: A search for the truth. *Journal of Consumer Behaviour: An International Research Review*, *2*(2), 196–202. Wiley Online Library.

Wu, D. (2019). Does social media get your attention? *Journal of Behavioral Finance*, *20*(2), 213–226. Taylor & Francis.

Yang, X. & Zhang, H. (2019). Extreme absolute strength of stocks and performance of momentum strategies. *Journal of Financial Markets*, *44*, 71–90. Elsevier.

Young, P. T. (1943). Emotion in man and animal; its nature and relation to attitude and motive. Wiley.

Yuan, L. I. & Dennis, A. R. (2014). The Happiness Premium: The Impact of Emotion on Individuals' Willingness to Pay in Online Auctions. *2014 47th Hawaii International Conference on System Sciences* (pp. 3120–3128).

Zeelenberg, M., Nelissen, R. M., Breugelmans, S. M. & Pieters, R. (2008). On emotion specificity in decision making: Why feeling is for doing. *Judgment and Decision making*, *3*(1), 18. Society for Judgment & Decision Making.

Zhang, X. (2006). Information uncertainty and stock returns. *The Journal of Finance*, *61*(1), 105–137. Wiley Online Library.

Zhang, X., Fuehres, H. & Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear." *Procedia-Social and Behavioral Sciences*, *26*, 55–62. Elsevier.

Appendices

Appendix 1: Trading strategy where holdings were daily Rebalanced and Turnover Calculation

There are 4 possible scenarios in this trading strategy which are explained below.

1. **No purchase and no sale:** Let's consider the following table as our example for this scenario

Table A 1: Example where we do not add or delete any stock from our portfolio

Sold Today	Bought today	Stock	return	Beginning of the day value	Return adjusted value	Equally weighted value at the end of the day	Buying/ selling on that day	Turnover (buy & sell)
No	No	A	-2.58%	25.29	24.64	25.50	0.86	**1.21**
No	No	B	0.27%	25.29	25.36	25.50	0.14	
No	No	C	0.03%	25.29	25.30	25.50	0.20	
No	No	D	5.60%	25.29	26.71	25.50	-1.21	
TOTAL				**101.17**	**102.01**	**102.01**		

In the above table, we start with four stocks that each have a value of $25.29, then at the end of the day, they either increase or decrease to the values shown in column 6. Column 7 shows the adjusted values, whereas column 8 shows the individual adjustments. Finally, in column 9, we have the daily turnover value of the portfolio. We find the daily % turnover by simply dividing the turnover value by the value of the index at the end of the day.

2. **Sale but no purchase:** Let's consider the following table as our example for this scenario

Table A 2: Example where a stock(s) leaves the portfolio, however, we don't buy any stock

Sold Today	Bought today	Stock	return	Beginning of the day value	Return adjusted value	Equally weighted value at the end of the day	Buying/ selling on that day	Turnover (buy & sell)
NO	NO	A	1.40%	15.08	15.29	17.69	2.40	**15.10**
NO	NO	B	-12.01%	15.08	13.27	17.69	4.42	
NO	NO	C	0.08%	15.08	15.10	17.69	2.60	
NO	NO	D	-3.34%	15.08	14.58	17.69	3.11	
YES	**NO**	**E**	**0.10%**	**15.08**	**15.10**	**0.00**	**-15.10**	
NO	NO	F	0.22%	15.08	15.12	17.69	2.57	
TOTAL				**90.50**	**88.46**	**88.46**		

In the above table, we only sell 1 stock (E) and don't buy any stock. Column 4 shows the return of the stock on a particular day. Columns 5 and 6 show the value before and after the inclusion of return. Column 7 shows the equally adjusted values after the sale of stock E. Column 8 shows the induvial turnover of the stocks where a negative sign show selling, and a positive sign show buying. The 15.1 that we got from the sale of stock E is adjusted to each stock so that each stock's ending value is equal to 17.69. Finally, column 9 shows the buy and sell turnover of the portfolio on a particular day. We find the daily % turnover by simply dividing the turnover value by the value of the index at the end of the day.

3. **Purchases but no sale:** Let’s consider the following table as our example for this scenario

Table A 3: Example where a stock(s) is added to the portfolio, however, we don’t sell any stock

Sold Today	Bought today	Stock	return	Beginning of the day value	Return adjusted value	Equally weighted value at the end of the day	Buying/ selling on that day	Turnover (buy & sell)
NO	NO	A	-3.82%	48.44	46.59	18.75	-27.84	
NO	NO	B	-2.65%	48.44	47.16	18.75	-28.41	
	YES	**C**	**0**	**0**	**0**	**18.75**	**18.75**	**56.25**
	YES	**D**	**0**	**0**	**0**	**18.75**	**18.75**	
	YES	**E**	**0**	**0**	**0**	**18.75**	**18.75**	
TOTAL				**96.88**	**93.75**	**93.75**		

In the above table, we buy 3 stocks (C, D, and E) and we do not sell any stock. Column 4 shows the return of the stock on a particular day. Columns 5 and 6 show the value before and after the inclusion of return. Column 7 shows the equally adjusted values after we add 3 more stocks into the portfolio. Column 8 shows the individual turnover of the stocks where a negative sign show selling and a positive sign show buying. Finally, column 9 shows the buy and sell turnover of the portfolio on a particular day. We find the daily % turnover by simply dividing the turnover value by the value of the index at the end of the day.

4. **Buy some stocks and sell some stocks:** Let's consider the following table as our example for this scenario

Table A 4: Example where we buy some stocks and sell some stocks

Sold Today	Bought today	Stock	return	Beginning of the day value	Return adjusted value	Equally weighted value at the end of the day	Buying/ selling on that day	Turnover (buy & sell)
NO	NO	A	-1.87%	8.54	8.38	8.59	0.21	**17.90**
NO	NO	B	0.81%	8.54	8.61	8.59	-0.02	
NO	**YES**	**C**	**0.00%**	**0.00**	**0.00**	**8.59**	**8.59**	
NO	NO	D	-0.97%	8.54	8.46	8.59	0.13	
YES	**NO**	**E**	**0.51%**	**8.54**	**8.58**	**0.00**	**-8.58**	
YES	**NO**	**F**	**1.25%**	**8.54**	**8.65**	**0.00**	**-8.65**	
NO	NO	G	-1.07%	8.54	8.45	8.59	0.14	
NO	**YES**	**H**	**0.00%**	**0.00**	**0.00**	**8.59**	**8.59**	
NO	NO	I	0.00%	8.54	8.54	8.59	0.05	
NO	NO	J	1.09%	8.54	8.63	8.59	-0.04	
NO	NO	K	4.07%	8.54	8.89	8.59	-0.30	
NO	NO	L	4.38%	8.54	8.91	8.59	-0.32	
NO	NO	M	-1.48%	8.54	8.41	8.59	0.18	
TOTAL				**93.93**	**94.50**	**94.50**		

In the above table, we buy 2 stocks (C, and H) and we sell 2 stocks (E and F). Column 4 shows the return of the stock on a particular day. Columns 5 and 6 show the value before and after the inclusion of return. Column 7 shows the equally adjusted values after we add 2 and remove 2 stocks from the portfolio. Column 8 shows the individual turnover of the stocks where a negative sign show selling and a positive sign show buying. Finally, column 9 shows the buy and sell turnover of the portfolio on a particular day. We find the daily % turnover by simply dividing the turnover value by the value of the index at the end of the day.

We find the daily % of the turnover and then annualise it.

Appendix 2: Trading strategy where holdings were daily rebalancing is minimized:

There are 4 possible scenarios in this trading strategy which are explained below.

1) **No purchase and no sale:** On a particular day, where we do not have any old stock leaving the portfolio or new stock entering our portfolio, we do not rebalance anything. Hence, we do not transact at all.
2) **Sale but no purchase:** distribute the total value of the sales equally across the stocks that we continue to hold in our portfolio.
3) **Purchases but no sale:** sell of Q/N of the value of each stock still owned and distribute the amount raised equally over the new stocks purchased (where Q is the number of new stocks purchased and N is the total number of stocks including the new ones purchased).
4) **Buy some stocks and sell some stocks:** This is a much more complicated scenario, and we take the following steps to complete it.

Step 1) We work out the value of the portfolio at the end of the day before any transacting (e.g., $500).

Step 2) We divide this value by the number of stocks in the portfolio after we have bought and sold (say we start with 4 stocks, sell 2 and buy 3 and hence end up with 5 stocks in the new portfolio). We divide the value of the portfolio, which is $500, by the number of stocks after trading, which is five, and we get $100. This tells us that we have to invest $100 in each of the new stocks that we are buying.

Step 3) We multiply the amount we calculate in Step 2 by the number of stocks we are buying, and we then have the amount of funds we need to raise to purchase the new stocks (in our example, we have to raise $300 in order to invest $100 in each of the three new stocks).

The formula for the above calculations is:

Amount to be raised = P (V/ (N+P-S))

Where,

V= Value of portfolio at end of the day before any transactions

N= number of stocks in existing portfolio

P= number of stocks to be purchased

S= number of stocks to be sold

Step 4) We calculate the amount of additional funds that has to be raised – this is the difference between the amount of funds needed to invest in the new stocks and the amount raised from the sale of stocks (in our example, we sell two stocks and assume that this raises $220, then we have to raise an additional $80 in order to be able to invest $300 in the stocks to be purchased).

Step 5a) This $80 is raised by selling an equal amount (in $) from the sale of the existing stocks which are not being sold (in our example, we started with 4 stocks, are selling 2 so there are two stocks remaining). Hence, we have to sell $40 worth of each of the remaining stocks. The formula for calculating the amount that we have to sell of the existing stocks = ((P(V/ (N+P-S))) – M)/(N-S)

where M is the amount raised by the sale of existing stocks. Our holdings in each of the stocks in our portfolio immediately after trading will be (i) for the existing stocks retained, it will be their value at the end of the day less $40, while for the new stock purchased, it will be $100. This amount must add up to $500 which was the value of the portfolio at the end of the day before any transacting took place.

Step 5b) The calculations in 5A are based on the presumption that the amount raised by the sale of stocks is not sufficient to fund the purchase of the new stocks. This will quite frequently not be the case, especially on those days when we are selling more stocks than we are purchasing. For example, assume that the sale of stocks in our example raises $350 which is $50 more than we need to acquire the new stocks. After transacting, we have 5 stocks (N+P-S) and so each stock is allocated an additional $10. In our example, the value of the existing stocks which are not sold will be increased by $10 while the holding in each of the stocks that are purchased will be $110. Again, this holding will add up to $500.