Do Emotions Influence Investor Behaviour?

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Abstract:

Despite much discussion in the psychology and marketing literature as to how emotions influence decision-making, this area of analysis has been largely neglected in the finance literature. We redress this important gap by using proxies for emotions drawn from the news and social media to evaluate their influence on investment decisions and ultimately asset pricing. We find strong evidence to support that emotions do influence investor decision-making and provide important insights into the nature of this relationship. In general, we find those positive emotions such as trust and optimism are more influential in shaping investors' reactions than are negative emotions. Finally, the emotions based on the news media listings have a greater influence on stock valuations than those based on social media listings.

Keywords: Emotions, Social Media, News Media, Investor Decision Making, Earnings Announcement; Asset Pricing

JEL Classification: G4, G14

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1. Introduction

This ongoing tension between cognitive and emotional impulses has long captivated the attention of researchers in psychology, dating back to Plato, who categorized human decision-making into emotions, cognition, and motivation. Eminent philosophers like Descartes (1989) and Hume (1985) have revisited this struggle in their seminal work, and the topic continues to be a subject of enduring interest to this day. Yet, until recently there has been little recognition and consideration for the role of emotions in financial decision-making. Rather the paradigm focuses on cognition and favours a framework where decisions depend on three primary factors: human rationality, the information available, and past experiences. This preference for adopting a rational expectations framework is understandable due to its mathematical elegance. While this approach has merits, it may not accurately reflect real-world decision-making where individuals face cognitive limitations and time constraints. Recent studies in psychology have shown that emotions can complement decision-making by narrowing the range of options and prioritising critical decision aspects (Hanoch, 2002; Brosch et al., 2013). Hanoch (2002) suggested that emotions should not be viewed as an alternative to the rational expectation framework; instead, emotion's purpose is to "supplement the themes emerging out of bounded rationality." (Hanoch, 2002, p.1)

The failure to recognise the significance of the role that emotions play in the finance literature is also at odds with anecdotal evidence that shows emotions can be very influential in setting asset prices and their impact on markets. The COVID-19 pandemic provided an excellent example of how emotions can significantly influence asset prices. Despite the massive falls and extreme volatility in global markets, RavenPack, a data service that applied 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. Thus, theoretical, and real-world evidence suggests that we must "understand what role emotion plays to have a complete theory of human rationality" (Simon 1983, p.29).

In this study, we take up the challenge of investigating whether emotions impact the valuation of a company's stock and provide the most complete and comprehensive empirical analysis of the impact of emotions on stock valuation. We examine two channels by which emotions might influence stock valuations: a channel where the investors' state of mind, conditioned by emotions, directly impacts the valuation they place on the company, and a second channel where emotions influence investor reaction to new information emanating from the company. Our findings support the proposition that emotions, as measured in news and social media, play an important role in how investors value stocks and react to information signals emanating from listed firms. We find that our aggregated measure across the individual emotions, *Aggregate_Emotion*, impacts investor decisions, as do the aggregate of each of the positive and negative emotions, and for many of the individual emotions[1]. 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 investors react to news emanating from the firm. Specifically, a positive emotion increases (decreases) the extent to which investors react to good (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. Our results are consistent with Wright and Bower (1992), which show that feelings impact people's subjective probability. People with a positive state of mind are optimistic and report higher probabilities for positive events and lower probabilities for negative events. On the other hand, people with a negative state of mind envision lower (higher) probabilities for positive (negative) events. However, we also establish that not all emotions are equal in terms of their influence on investor decision-making, with several of them (e.g., fear) having little or no impact on these decisions.

Our proxy for investor emotions is derived through textual analysis of news and social media postings. Research has shown that news and social media postings provide an accurate and timely record of how investors feel about a specific company and the state of the market (Uhl, Pedersen and Malitius, 2015; Sul, Dennis, and Yuan, 2017; Gan et al., 2020). With the rapid growth of social media over the 20 years covered by our study, it would be interesting to ask which of the two media has the greater influence on stock valuations. We found mixed results on this issue over our entire sample. In some instances (e.g., love/hate), we find that social media emotions exhibit a greater impact on asset prices. In other instances (e.g., stress), it is the news media that exerts the greater influence. When we decompose our 20 years of data into three sub-periods, we find that the influence of emotions on stock valuations has increased over time, with the emotions emanating from the news media still maintaining, although the influence from that emanating from the social media is growing at a faster rate.

[1] 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.

The study contributes to the literature in many areas. First, we contribute to the behavioural finance literature by demonstrating the causal relationship between investors' emotions and stock returns. The results provide empirical validation for Shu (2010), who suggested that the level of emotion impacts investors' valuation of companies. Previously, there has been limited research on how emotions have affected short-term stock returns (Griffith et al., 2019; Vamossy, 2020, Cao et al., 2022). Our results confirm this direct link between emotions and returns. Moreover, we show that the association between emotions and asset prices also flows through an indirect channel, where the impact of news on valuation will be influenced by the emotions experienced by investors at the time of the news.

Second, the findings also add to the growing literature that identify external factors that influence how investors react to earnings news. Studies have shown that the magnitude of the investors' response to earning surprise can be influenced by external conditions such as market-wide ambiguity (Bird and Yeung, 2012; and William, 2014) and information uncertainty (Almakti et al., 2020). We add individual emotions to this list by demonstrating that prevailing emotions determine the extent to which investors react to news emanating from the company (or relative sensitivity of announcement returns to the magnitude of the earning surprise).

Third, the study 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 financial decision-making process. Research has shown that media and social media can: influence the purchasing decision (Deloitte, 2008), influence the volume of stock market trading (Peress, 2014) and stock price fluctuations (Strycharz et al. 2018) and make accurate predictions of future company announcements (Bartov et al., 2017). Our results add to the literature by showing emotions garnered in mass media and social media provide an accurate gauge of investors' emotions that can influence asset prices.

Fourth, the evidence that emotions influence asset pricing represents yet another challenge to the Efficient Markets Hypotheses (EMH). In the rational expectations world that underlies the EMH, there is no room for emotions to influence investor decision-making. The fact that we have identified both direct and indirect channels though which emotions arise suggests that the impact of pricing is always at the mercy of individual emotions.

In the next section of the study, we provide a more detailed background on the literature regarding emotions' influence on investor decision-making in general, and on financial decision-making. This is followed by an outline of the research questions we examine, and then a discussion of both the data and research design employed. Our empirical findings are then presented, and we conclude with a section that provides an evaluation and discussion of the importance of our major findings.

2. Literature Review

2.1 Background

So, what are emotions, and how do they impact decision-making? In layman's terms, emotions are feelings states such as optimism, joy, trust, fear, stress, gloom, anger, love, and hate. These "feelings" are triggered as a psychological reaction to a stimulus, such as news or a thought (Yuan and Dennis, 2014). Often emotions are multifaceted and characterised by physiological reactions such as the sudden increase in the heart rate, excessive sweating due to stimuli, or coping behaviour such as attacking or running away from a situation (i.e., ‘fight or flight’). In fact, if we look at the literature on emotions, we find that emotions have been described as bodily feedbacks (James, 1894), facial expressions (Chovil, 1991), cultural symbols (Averill, 1974), and cognitive interpretations of arousal (Breugelmans et al., 2005).

Emotions are usually acute and are relatively short experiences (Wilson et al., 2001). For example, emotions can be triggered by someone (e.g., you are angry with your friend) or something (e.g., you regret buying a particular product). Yet emotions are not everlasting; once the stimulus that triggered the emotion(s) disappears, the emotion(s) will also gradually dissipate (Wilson et al., 2000). This short and intense nature differentiates emotions from other varieties of affects, such as moods and sentiment that maintain over longer time periods. Additionally, emotions are "cognitively impenetrable", which means once an emotion is triggered, a person cannot choose between having or not having the emotions (Frijda, 1986). To further complicate matters, emotions can often occur subconsciously or at a low level of consciousness (Izard, 2009). The cumulative effect of these characteristics may lead investors to make financial decisions based on a sudden surge of emotions over which they may have little control or awareness.

In the past thirty or so years, we have seen increased interest in understanding emotion's role in economic decisions (Smith and Lazarus 1990; Isen, 2000; Loewenstein et al., 2000; Keltner & Lerner, 2001; Lucey and Dowling 2005; Keltner & Lerner, 2010). Central to this investigation lies the pivotal question of whether emotions sway decision-makers to adopt markedly divergent choices compared to those driven by cognitive evaluations (i.e., standard rational utility framework). Lowenstein et al. (2001) argue that emotions can influence individuals' cognitive evaluations of risks, and thus generate different responses to probabilities and outcomes. They showed that emotional reactions can influence and may even override cognitive decisions involving risk and uncertainty. Moreover, the influence of emotions is greater in complex decisions (such as investment) that require greater cognitive processing (or thinking) (Forgas,1995). Pham (2006) argued it is not exceptional for individuals to feel anxious when making a difficult decision. Anxiety and the fear of regret have been found to drive individuals toward making a safer choice rather than a potentially more lucrative yet more risky one (Lerner et al. 2015). Studies by Bachara et al. (1999) and Damasio (1994) provide further support for the important role of emotion in decision making by demonstrating that neurologically impaired individuals, unable to feel emotion, make suboptimal decisions.

Shu (2010) provided a theoretical foundation that links investor emotions and asset prices. Shu (2010) demonstrates that minor emotional variations can lead to financial market fluctuations in a simple general equilibrium asset-pricing model where time preference and risk attitude are mood factors. In particular, improvements in investor emotions increase asset prices. Our analysis is consistent with Shu's predictions; we examine many emotions experienced and how they impact the individual's reaction to new information concerning earnings. The underlying logic to our model is that the emotions expressed in the social and news media proxy for investor emotions and that these emotions will influence the way investors value stocks and respond to the information signals.

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 here 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 (e.g., anger and fear). In this study, we draw upon this concept and divide emotions into positive and negative partitions, and then 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 and Keltner, 2001). Sambrano et al. (2021) argued that similar to happiness, anger can also trigger a less pessimistic view of an event in an individual. 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. Hence, we also investigate whether the emotions of the same valence impart a similar effect on individuals' financial decision-making. To the best of our knowledge, we provide the most comprehensive study to date of how emotions impact investor valuations of companies.

2.2 Emotions and its impact on Asset Prices

Early work on the influence of emotions on asset prices focus on the impact of incidental emotions, feelings generated by one event (e.g., bad weather or a favourite sports team losing) can carry over to influence the decisions of another event. Saunders (1993) found that cloudy days bring on negative moods, impacting investors' trading behaviour, and are associated with lower returns. Edmans et al. (2007) found that the elimination from the world cup is associated with abnormal returns of 49 basis points. Abudy (2022) et al. study the effect of victory in the Eurovision context where sentiment is found to be positive in the winning nation and derives investors an abnormal first trading day return of 0.35%.

In the past several years, we have witnessed an increasing interest in the link between integral emotion (direct emotion) on prices (Griffith et al., 2019; Vamossy, 2021; Taffler et al., 2021; Cao et al. 2022). Using the Chinese stock market bubble as a background, Taffler et al. (2021) highlight the link between emotions experienced by investors and stock market performance in the boom/bust cycle of an asset price bubble. Griffith et al. (2019) used a VAR framework with Thomson Reuters MarketPsych Indices (TRMI) data and based on a limited number of emotions evaluated at the market level found limited evidence to suggest that emotions have a small impact on prices. In a recent study, Cao et al. (2022) show that an index that measures anger, "reliably" predicts index futures return. Vamossy (2021) measured average emotions in the 10 days leading up to earning news announcements and found that high emotions before the announcement may lead to a reversal in the announcement period. The intuition is that investors' emotions are influenced by the leakage of information about the upcoming earnings announcement, and so the market prices already reflect this emotions/earning information. Unlike Vamossy (2021), we argue that emotions are short lived and fleeting. Accordingly, 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 period). We show that the level of emotion immediately before the announcement is positively related to abnormal returns in the announcement period.

Two recent papers have examined the relationship between emotions and stock returns by looking at the return sensitivity of stocks to emotions (Hirshleifer et al., 2020, Bin Hasan et al., 2022). Hirshleifer et al. (2020) found evidence that aggregate and cross-sectional return seasonality are at least partly caused by seasonal variations in investor feelings. Bin Hasan et al. (2022) estimated individual firm-level stock emotion betas by employing 60-month rolling regressions of excess stock returns on a market emotion index and found that a long-short portfolio of buying high-beta stocks and shorting low-beta stocks could yield an alpha of approximately 7%. While both papers demonstrate a predictable relationship between market conditions (market emotions/moods) and the returns of a specific type of stocks, they do not provide direct evidence of how firm-level emotion impacts trading behaviour and thus, prices.

2.3 Emotions versus Sentiment

Before moving to our data and analysis section, it is essential to differentiate emotions from sentiment to fully appreciate the contribution of this analysis. Emotions and sentiment are fundamentally distinct terms despite their common misuse in the finance literature as being interchangeable.[2] We have already learned that emotions are spontaneous, acute, fleeting and occur at a low level of consciousness. Sentiment is a product of cognitive bias, while emotions result from biological processes (Rapp, 2019). Conversely, sentiment is formed gradually through our actions when our instincts express themselves the same way. Repetitive action form habits, and the combination of instincts and habit form sentiment. The reasons that these terms are often erroneously used interchangeably is because few studies define sentiment. As such, any kind of available data has been regarded as sentiment as long as someone is convinced that these data depict the market sentiment in some way (Bormann. 2013).[3]

Sentiment proxies such as the Baker and Wurgler Index does a reasonable job in modelling this "readiness to respond" nature of sentiment. However, there are several reasons that the conceptual differences between emotions and sentiment as to why existing proxies of sentiment do not capture

[2] For a recent example of the failure to distinguish the difference between sentiment and emotions see Griffith et al. (2019), who despite basing their analysis on TRMI emotions data, frequently switch between using the words sentiment and emotions when discussing their findings.

[3] There is an evolving literature on the effect that sentiment has on asset pricing, with a range of proxies having been used for sentiment: some based on market and economic variables (Baker and Wurgler, 2006), others drawn from investor surveys (Greenwood and Shleifer, 2014), and still others determined using textual data (Garcia, 2013).

the influence that emotions have on asset valuation. First, think for example of the anger and often frenzied actions associated with a "road rage" incident. These short sharp emotional episodes are unlikely to be captured by sentiment measures that are typically less granular (e.g., the monthly Baker-Wurgler Index)[4]. Second, the presence of thoughts and cognition associated with sentiment allows individuals to control and regulate their decision-making (when compared to emotion) more easily. The studies that provide evidence of trained institutional investors being less susceptible to investor sentiment than retail investors are a case in point. (e.g., Tetlock, 2008 and Rapp, 2019). On the other hand, emotions are spontaneous and can occur at a low level of consciousness beyond our cognitive awareness. It follows that immunising decision-making to the influence of emotions becomes much more challenging, irrespective of the investor's sophistication (Rapp, 2019).

In summary, emotions and sentiment are quite distinct personal traits, and consequently, the findings from the literature as to how sentiment influences asset pricing cannot be extrapolated to emotions. Emotions and sentiments are recognised in the behavioural science literature as being quite distinct, the methods employed to measure sentiment cannot be construed as appropriate for measuring emotions, and the statistical properties are quite different; with sentiment trending over several months while emotions are represented by short-term spikes.

3. Research Questions

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 1, is that emotions *and* new information will play a role in determining investor expectations and 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 investors' reactions to the release of earnings by analysing the behaviour of a company's stock price around the time of the earnings release.

<<INSERT FIGURE 1>>

[4] In Appendix 1, we provide evidence to support the proposition that emotions behave quite differently to sentiment, with emotions exhibiting very short-term spikes while sentiment exhibits trends that continue for extended periods of time.

One of the two channels we examine is the direct impact that an investor's state of mind has on corporate valuations (Griffith et al., 2019; Vamossy, 2021, Cao et al. 2022). Our model also incorporates an indirect channel, to clearly show how emotions influence perceptions and shape responses to new information. We hypothesise that emotions influence our perception and our reactions to news. For example, anger may increase risk-seeking behaviour (Gambetti and Giusberti 2012), while fear may induce more pessimistic and risk-averse behaviour in decision-makers (Lerner and Keltner, 2000,2001). We test this second channel by focusing on earnings announcements as the information source, which has the advantage of being regularly announced at scheduled points in time by all firms and has well documented implications for stock market reactions. The fact that stock prices react to unexpected earnings announcements is documented in the seminal Ball and Brown (1968) study, first providing evidence on what came to be known as the post-earnings announcement drift (PEAD). Numerous studies have since confirmed that the stock price of companies on average underreacts at the time of an earnings announcement, and this is then 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 and Theobald, 2004); and liquidity (Chordia, Huh, and Subrahmanyam, 2009). Others have examined how market factors impact on investor reactions to information signals such as market sentiment (Baker and Wurgler, 2006; Bird et al., 2014) and market uncertainty (Bird et al., 2014; Williams, 2015).

A challenge for empirical research on emotions has always been the search of an appropriate method to measure investor emotions. Advances in computing and computational techniques have resolved this problem, allowing textual analysis to detect emotion in writing. By applying the use of semantics to social and news media postings, researchers have been able to provide an accurate gauge of human emotions and how they can impact financial markets. It is very well recognised that emotions and feelings can be expressible in language. Several studies have shown textual analysis captures emotion in 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), Pellert et al. (2022)). Pellert et al. (2022) compared emotion metrics derived from social media postings with self-reported emotions from the UK's YouGov survey. They found a high correlation between the textual analysis-based measures of emotions and self-reported feelings of 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.

In this study, we employ nine emotions indices generated by TRMI data derived from the textual analysis of both news and social media postings. The underlying logic to our model is that the emotions expressed in the social and news media proxy for investor emotions, which will influence the way investors value stocks and respond to the information signals. In our case, that information that we consider is earnings announcements.

We propose that emotions expressed significantly impact investor decision-making and this proposition forms the basis of our first research questions.

> 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:
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> 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)?

Since TRMI source information from News and Social media postings, it allows us to examine the relative importance of these media outlets. 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% from 2005 to 72% by March 2021 (Pew Research Center, 2021). To investigate the relative influence of these media sources on company valuation, we add two auxiliary questions to our analysis.

> Question 2: Which of the two media sources that provide proxies for individual emotions has the greater influence 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 nine 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.
- Access data on emotions that extends over thousands of companies collected on a minute-by-minute basis spanning over 20 years.

4. Data

Our sample period extends from the beginning of 1998 to the end of 2017, with the universe being restricted to stocks listed on the S&P500 The information regarding actual earnings and financial analysts' earnings forecasts for each stock is gathered from the I/B/E/S database. The accounting data, including reported earnings, is obtained from the CRSP/COMPUSTAT merged database and sourced through WRDS. WRDS is the source of the equity market's CRPS return and price data. We acquired the Implied Volatility Index (VIX) data for the market from the CBOE.

In line with prior literature, we have winsorised the characteristics for each stock at the 1st and 99th percentiles to eliminate outliers' impact. In addition to being a member of the S&P500, we have also applied a set of stringent criteria to determine the eligibility of firms for inclusion in our sample:

1) The price of the share, as reported in Compustat, had to be greater than $1.
2) To eliminate the firms with low liquidity, we include only those with a market (book) value greater than $5 million at the end of quarter "t-1".
3) Daily returns are available on CRSP from "t-1" to "t+1", where "t_0" is the announcement day.
4) The earnings announcement date is reported both in I/B/E/S and Compustat. To be included in the sample, the difference between the I/B/E/S report date and Compustat report date should not be more than one calendar day.
5) Firms that did not have any analysts' earnings forecast data were also removed.

Finally, we source the data on nine distinct emotions from the Thomson Reuters MarketPysch Index (TRMI) database[5] (which extends back to 1998) and construct three additional emotion measures; aggregate emotions, aggregate positive emotions, and aggregate negative emotions.[6] Peterson (2016) provides an extensive discussion of the TRMI. A significant advantage of utilising this distinctive dataset, sourced from a reputable professional data provider, is that it does not suffer from the limitations of other textual analysis data derived from a restricted range of media sources, a narrow set of assets, and truncated sample periods. Several studies have already confirmed the effectiveness and accuracy of this database. For example, Michaelides et al. (2015) found that variation of the TRMI metrics matched the data of manually collected sovereign downgrade news. In a separate study, Michaelides et al. (2019) confirms that the TRMI sentiment index is consistent with manually constructed FX currency-related news.

TRMI data is obtained by scanning two million social media sites (e.g., Yahoo! Finance, Stocktwits, Blogger, Seeking Alpha, Google News)[7] and 50,000 professional news sites (e.g., *The Wall Street Journal*, *The New York Times,* and the *Financial Times*. Each posting on these sites is screened to determine its financial relevance to the company to which it relates. If it passes this filter, the posting is processed using the TRMI's linguistic software to determine how much (if anything) it contributes towards the score for each company and for each of the emotions. The result of this process is that we have a score for each of the nine emotions calculated on a minute-by-minute basis from each social media and the traditional news media.

The TRMI emotion scores are bipolar (-1 to 1) or unipolar (0 to 1). For example, Optimism is bipolar as it can take on positive or negative values, while Joy is unipolar as it can only be positive. Table 1 provides an overview of all the emotions utilised in the study. There are also 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. Following Ryan and Giles (1999), we have addressed the issue of missing values by using a technique of carrying forward the previous observation. As discussed earlier, we source nine different positive and negative emotions from TRMI. We calculate the aggregate positive and negative emotions based on a group of positive/negative emotions. For the Aggregate Positive emotion score of firm 'i' on day 't', we take

[5] https://a-teaminsight.com/blog/thomson-reuters-adds-sentiment-data-on-companies-to-its-marketpsych-indices/
[6] There are 34 indices of emotion in the Thomson Reuters MarketPysch Index (TRMI) database. We have chosen nine of these emotion indices in our study based on evidence from past literature indicating that these emotions are most likely to influence decision-making. For example, we included anger as Lerner and Kelter (2000) show that anger and fear can influence individuals' risk preferences. The authors found that anger tends caused individuals to be more risk-taking, while fear tends to make individuals more risk-averse in making decisions.
[7] Thomson Reuters claims that the TRMI index covers 30% of all social media sources.

the average score of Optimism, Joy, Trust, and Love/Hate. We remove any observations with less than two positive emotions to make up the aggregate positive emotion. Similarly, for the Aggregate Negative emotion score of firm 'i' on day 't', is the average score of Stress, Gloom, Fear, Anger, Conflict, and Violence. Finally, the Aggregate Emotions score is the sum of the score for Aggregate Positive and Aggregate Negative.

For this study, 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 "emotion" relates to the data collected between 4 pm (market close) on January 10th, 2008, and 4 pm on January 11th, 2008. The next set of scores for "emotion" would be based on the data collected between 5 pm on January 10th, 2008, and 5 pm on January 11th, 2008. Our emotion measure for each emotion is the score as at 4 pm each day measured over the previous 24 hours.

5. Research Design

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[8] Consistent with standard practice in the literature, we use a two-day window (t=0 and t= +1) to calculate the returns over the announcement period.

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

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

(Eq. 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" measured for each firm "i" as:

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

[8] If an announcement is made on a weekend or a public holiday (i.e., when the market is closed), we move the announcement day to the next trading day.

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[9].

$$UE_i = \frac{Actual\ Earnings\ per\ Share_i - Latest\ Median\ Expected\ EPS_i}{Actual\ Earnings\ per\ Share_i} \quad \text{(Eq. 1.1)}$$

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.[10]

We include numerous control variables in our study chosen because they have been found in previous studies to be correlated with returns. These include firm size (Bernard and Thomas, 1989), earnings volatility and book-to-market (Hirshleifer, Lim, and Teoh, 2009), Friday (Hung, Li, and Wang, 2014), beta and loss (DeFond, Hung, and Trezevant, 2007), FQ4 (Sun, 2015), VIX (Bird et al., 2014), and momentum (Boehmer and Wu, 2013). 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.

[9] We also scale the unexpected earnings by price and by median consensus analysts' forecast. However, the results are chosen because they have been found to be quantitatively similar.
[10] In 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.

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.

Another 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 and 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 any potential endogenous relationship between emotions and stock returns did not influence our findings.

Further, we have also 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 this drives our results. The 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 issue, and make our model more robust, we follow Petersen (2009) and cluster the standard errors 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 1 to incorporate the separation of PUE and NUE. The expanded equation is as follows.

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \sum \beta_k Control\ Variables + \sum Effects \quad + \varepsilon_{i,t} \ldots \text{(Eq 2)}$$

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 and abnormal returns, and the extent to which the reaction of investors is affected by (1) the level of emotion before the announcement and (2) change in emotion over the event window. To incorporate this, we expand Equation 2 as follows:

$$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t-1,1} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t} \ldots \text{(Eq. 3)}$$

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 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 nine individual and three aggregate emotion measures, and for each of our information sources (social and traditional news combined, social only, and traditional news only). Suppose emotions have an impact on how investors respond to earnings announcements. In that case, 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 $\beta_3 + \beta_5$ in Equation 3. In the case of PUE, we expect high positive emotions to increase the market response, whereas high negative emotions would decrease the market response. We can directly test these expectations by observing the sign and significance of $\beta_4 + \beta_6$ in Equation 3. The other two variables of interest are $FEt_{i,t-1}$ and $\Delta FEt_{i,t-1,1}$which represents 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 indicates that the level of and/or the direction of emotions directly impacts the abnormal returns.

A summary of the variables included in our analysis is set out in Table 1. An analysis of this data that PUE represents about 75% of the sample, but the magnitude of NUE is about twice that of PUE[11]. However, we also see that the standard deviation of NUE is much higher than the standard deviation of PUE. Our analysis further suggests no significant difference exists between the level of emotion emanating from social media and the level of the news media. There is undoubtedly more Joy and Love/Hate generated by social media, although this is somewhat balanced because 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.

<<INSERT TABLE 1>>

6. Empirical Results

This section presents our research results on the impact of news and social media emotions on company valuation. Our study investigates the direct effect and how the market responds to information disseminated by the company.

Market Reaction

As the first step towards investigating whether emotions impact 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 1 to our data, and we reported in Table 2 (Panel A). The coefficient reported for unexpected earnings (β_1=0.024***) clearly indicates a significant reaction to the earnings announcement (i.e., good news has a positive impact on the value of a company,

[11] The detail of this data summary is available from the authors.

and bad news has a negative impact)[12]. The sign of the coefficient attached to each control variable is generally as expected. For example, a size and value effect is apparent in the announcement period. 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 return reversal is consistent with Vamossy (2021) findings, which document a similar return turnaround in the announcement period.

Next, we apply Eq. 2 to our data to separate our unexpected earnings into bad news (NUE) and good news (PUE). The coefficients reported in Table 2 (Panel B) for NUE (β_1=0.017***) and PUE (β_2=0.034***) confirm that the investors react to both negative and positive news, with the response being twice as great for a quantum of good news than it is for a quantum of bad news. On balance, this finding is consistent with that of most other papers (e.g., Lu et al., 2013)

<<INSERT TABLE 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, few have investigated the impact of emotions on the relationship between earnings announcements and stock price adjustment (Vamossy, 2021, Griffith et al., 2019). In this study, we investigate the extent to which a wide range of emotions plays a role in determining asset values directly or through the market response to the release of new information. Through this approach, we can effectively measure how emotions, as captured by news and social media coverage, affect investor decision-making. We estimate Equation 3 using data on our nine individual emotions measured at the company level and derived from the social media, the news media, and these two media sources combined. As indicated in Table 1, we divided the various emotions into four positive and five negative emotions. We have also calculated aggregate positive emotions, which is the aggregation of the four positive emotions,

[12] It must 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.

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 into how Aggregate_Emotion, the composite of positive and negative emotions, impacts market valuations. We next examine the positive component and the negative component of the *Aggregate_Emotion* score separately. As a final step, we examine how each of the nine individual emotions impact company valuations. Through this rigorous analytical framework, we can explore in depth the emotional drivers of investor behaviour and undertake a more thorough analysis of emotions' role in influencing investor decision-making and asset prices.

Aggregate_Emotion

Our equivalent is *Aggregate_Emotion* 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 3 (Panel A), 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* proxied by listings on 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 = 0.017*** from Table 2, Panel B). 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 = 0.012** < 0.017***). 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 = 0.021*** > 0.017***). Consistent with expectations, our analysis shows that a negative earnings surprise leads to a downward revision of a company's stock price. We find that the magnitude of this downward adjustment is relatively less pronounced when negative earnings are announced at a time of high Aggregate_Emotions. However, it is worth noting that the observed difference in the degree of adjustment is statistically insignificant.

We see from Table 2 Panel B that the coefficient for PUE across the whole sample is 0.034***, which confirms that on average, there is a positive reaction to a positive earnings surprise. In relation to Table 3 (Panel A), 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 = 0.058** > 0.034***). 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 emotions are very positive. However, if we look at the market reaction to good earnings news released when Aggregate_Emotion is low, we see that the market reaction is much lower than it is in more typical times (PUE = 0.008 < 0.034***). Indeed, we find that investors effectively ignore good earnings news released at a time when Aggregate_Emotion is low 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 (0.050***) is highly significant, demonstrating that emotions have a significant impact on how investors respond to good 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 influence. 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 influence but to a lesser extent than was the case for the direct path.

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. To better understand the impact of emotions, we break emotions down into a positive and negative component (i.e., valence) to better understand how emotions influence investors' decision making.

Our findings for aggregate positive emotions and aggregate negative emotions are reported in Table 3 of Panel B and Panel C. We start by considering the direct impact that aggregate positive and negative emotions have on market valuations. Our analysis of emotive tones extracted from news and social media reveals that both aggregate positive and negative emotions bear a statistically significant influence on asset prices, with positive emotions positively linked to a surge in market valuations, while negative emotions exhibit a negative influence on prices. Further, the aggregate positive emotions have 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 emotions, as proxied by the news media, have far more significant influence through the direct channel on investor behaviour.

<<INSERT TABLE 3>>

When measured across the news and social media combined, we find that both aggregated positive and negative emotions have the expected impact on how investors react to the release of earnings news. Positive emotions significantly decrease the impact of bad news and increases the impact of good news. In contrast, negative emotions significantly increase the impact of bad news and reduces the impact of good news. Our findings emphasise 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 see some weakening in the findings when we examine the influence of the aggregated positive and negative emotions as proxied by either the social media or the news media, alone. For example, we found using the combined measure that aggregated negative emotions diluted the impact of a poor earnings announcement but when we examine the influence of the aggregated negative emotions score as measured from each of the news and social media, we find the sign on the relationship is still negative but that it is no longer significant. Overall, we find as with *Aggregate_Emotion,* that it is the emotions emanating from the news media that has the greater influence on investor behaviour.

Individual Emotions

We have found strong evidence from our examination of the aggregate emotions score and its positive and negative sub-components that emotions have a strong influence on investor decision-making. We will now dig deeper to examine the extent to which the findings for the aggregated measures are driven by each of the nine individual emotions included in the study. We will first examine the four positive emotions (optimism, joy, trust, love/hate), and then the five negative emotions (stress, gloom, fear, anger, and conflict).

Individual Positive Emotions

When we examine the combined individual positive emotions across both the news and social media, we find that all four of them have the expected positive direct impact on stock valuations with that of trust being the strongest and that of love/hate being the weakest[13]. In the case of both optimism and trust, it is the emotion emanating from the news media that has the greater influence whereas with joy and love/hate the news media would seem to have little or no influence and it is the social media that has the grater direct impact.

We find strong support for the existence of the second channel through which emotions influence the extent to which investors react to unexpected earnings news. However, there is variation in the strength of this relationship across each of the four individual positive emotions. In the case of a positive earnings surprise, each of the four emotions determined using a combination of the news and social media have the expected impact of boosting the response to good news. This influence is most substantial in the case of optimism and trust and not statistically significant for joy and love/hate. Similarly, with negative earnings surprise, we find the expected result that each of the four positive emotions serve to dampen the extent of the investor response to bad earnings news. In the case of optimism, joy, and love/hate, the influence of the positive emotions is so great that it results in no negative price reaction for reporting poor earnings news. Overall, the two media sources are of fairly equal influence in the case of optimism, joy, and trust. However, in the case

[13] The tables on which this discussion is based is contained in Appendix 2.

of love/joy it is the social media that has the greater influence which is consistent with our finding for this emotion when considering the direct impact.

Individual Negative Emotions

In contrast to our findings for the four positive emotions, not all the five individual negative emotions contribute to the findings that we have previously observed at the aggregate level[14]. For example, we have found that the emotion score obtained from aggregating the 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 each of the social and news media make an important contribution to our finding that stress, gloom, and conflict each have a direct impact on stock valuations, with the news media having the stronger influence.

When we turn our attention to how individual negative emotions influence investor response to unexpected earnings announcements, we find that stress, gloom, and conflict each play an important role in shaping investor response to positive earnings news by dampening the impact that good earnings news has on stock valuation. In the case of negative earnings news, it is only stress and gloom that impact on investor behaviour by causing a greater negative reaction to bad news. Importantly, we find that with fear or anger, we have two emotions which have no influence on how an investor responds to the release of unexpected earnings. When it comes to determining which of the two media sources has the greater influence on investors when it comes to responding to negative emotions, we find it the news media that has the greater influence in the case of conflict,

[14] The information on which this discussion is based is contained in Appendix 3.

it is the social media in the case of conflict, while two media sources have a similar influence in the case of gloom.

Although we provide strong evidence that the aggregate of the nine individual emotions (i.e., *Aggregate_Emotion*) impact on the decision-making of investors and so corporate valuations, it is clear that not all the five individual negative emotions contribute to this outcome. Importantly, we find that neither anger nor fear has any discernible influence on how the decisions made by investors. Of these two emotions, the finding of the irrelevance of fear is perhaps the more surprising as statements are often made as to how stock prices are moved by 'greed' and 'fear' (Breaban and Noussair, 2018). Indeed, Griffith et al, using the same TRMI data found much weaker evidence for the influence of emotions with fear being the most influential of the emotions that they examined. However, they used a time series test, and examined only a limited number of emotions with a much smaller data set. We surmise that in our case the supposed impact of fear is captured by stress, and even gloom, which results in fear not appearing to have a significant influence on investor decision- making[15].

Impact of Emotions Over Time

Our data covers 20 years, over which there have been dramatic changes in the media landscape, especially with the growth of social media. At our starting date of January 1998, social media was in its infancy, with the first recognisable social media site, Six Degrees launched 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 continued with rapid growth. Hence, the first sub-sample that we have chosen extends from January 1998 to December

[15] We conduct additional checks to ensure the robustness of our reported findings, focusing on two crucial proxies used in the study: unexpected earnings and abnormal returns. For unexpected earnings, we repeated the analysis using different scaling methods, such as scaling by the median consensus analyst forecast and by price and found that the results remained quantitatively similar to our main analysis. Regarding abnormal returns, we recalculated them using the market model to capture excess returns, and once again, our major findings remained unchanged.

2005, which we suggest is a period that corresponds to the early development phase of electronic social media.

YouTube was founded in 2005, creating an entirely new way for people to communicate and share digital materials globally. It was quickly followed in 2006 by both Facebook and Twitter. Hence, we have chosen January 2006 as being the date when social media began to be established as a wide-ranging communications channel. For our purposes, April 2013 is another critical date. During this month, the Securities and Exchange Commission (SEC) announced that companies could now use social media to distribute 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 a summary of the impact that *Aggregate_Emotion* has on investor responses to media postings during each of the sub-periods[16]. Our findings suggest the emotions emanating from the media as a proxy for investor emotions has had a direct influence on how investor value stocks over our entire sample period, and in each sub-period. However, the reported coefficients indicate that the impact of *Aggregate_Emotion* has considerably strengthened over the period. When we examine both the absolute level and change of *Aggregate_Emotion* over time, we can see that the news media continues to have the greater influence social media but with social media's influence increasing over time.

<<INSERT TABLE 4>>

We obtain quite different results when we examine the influence of both types of media over time in relation to 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

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

news. In contrast, 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 has 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 stronger in the case of the reaction to good earnings news.

In summary, the *Aggregate_Emotion* emanating from both social media and the traditional news has influenced investor behaviour over our 20-year sample period. On balance, the level of influence exerted by the media has increased over time and not surprisingly, the greatest growth being associated with the *Aggregate_Emotion* emanating from social media.

7. Conclusion

In this study we use nine emotion measures extracted from a textual analysis of the news and social media postings as proxies for investor emotions. We find that at the aggregated level, there is strong evidence to support that emotions directly impact market prices and can also influence how investors react to information signals. Positive emotions directly boost security prices and the market response to good news while dampening the response to bad news, while negative emotions directly dampen security prices and the response to good news while boosting the market response to bad news.

When examining the impact of the individual emotions, we find clear evidence that some emotions have greater impact on asset prices than others. When we examine the four positive emotions, for example, Optimism and joy clearly have a powerful direct and indirect influence on asset pricing. On the other hand, trust seems to have lesser impact on prices. For example, a higher level for trust does not influence how investors react to poor company performance. For Love/Hate, we find that this emotion does affect how investors respond through the indirect channel, but it has a weak direct impact on security pricing.

The influence of the individual negative emotions proves to be weaker and even more variable than was found to be the case for the positive emotions. Stress, Gloom, and Conflict all directly impact security pricing, whereas the other two negative emotions have no impact. Stress and Gloom each strongly influence 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 impact investor behaviour most, with fear having little or no influence at all.

We also examined the relative influence of each of the two media sources, including how this might have changed over time. In the early years of our sample, the proxy derived from the news media was the more influential of the two media sources, which is a dominance that it maintained over the whole sample period, although the influence of social media has grown most in a relative sense in the intervening years.

The study represents the most comprehensive analysis of how investor emotions influence their decision-making. The findings provide clear evidence that emotions play an important role in asset pricing, which has significant implications for how assets are priced in markets and questions the extent to which markets can be assumed to be efficient. The study has clearly concentrated on the role played by emotions in influencing investor behaviour around the time of the release of an earnings announcement. It would be informative to extend this analysis to the post-announcement period to determine how permanent are any mispricings caused by emotions. This would not only be invaluable in terms of the insights it provides as to the efficiency of markets but also as to the opportunity to use information relating to emotions as the basis for profitable investment strategies.

Another line of future research would involve extending the analysis to examine the influence of emotions to other markets (e.g., debt markets and currency markets) and to its impact on particular corporate actions (e.g., mergers and takeovers, and initial public offerings). Yet another line of research would be to dig deeper to examine whether different investor groups and/or different types of stocks were more influenced by emotions than others. For example, whether it impacted retail investors more than institutional investors, male investors more than female investors, small cap stocks more than large cap stocks and/or value stocks more than growth stocks,

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Figure 1: Proposed impact of emotions and new information on investors' expectations

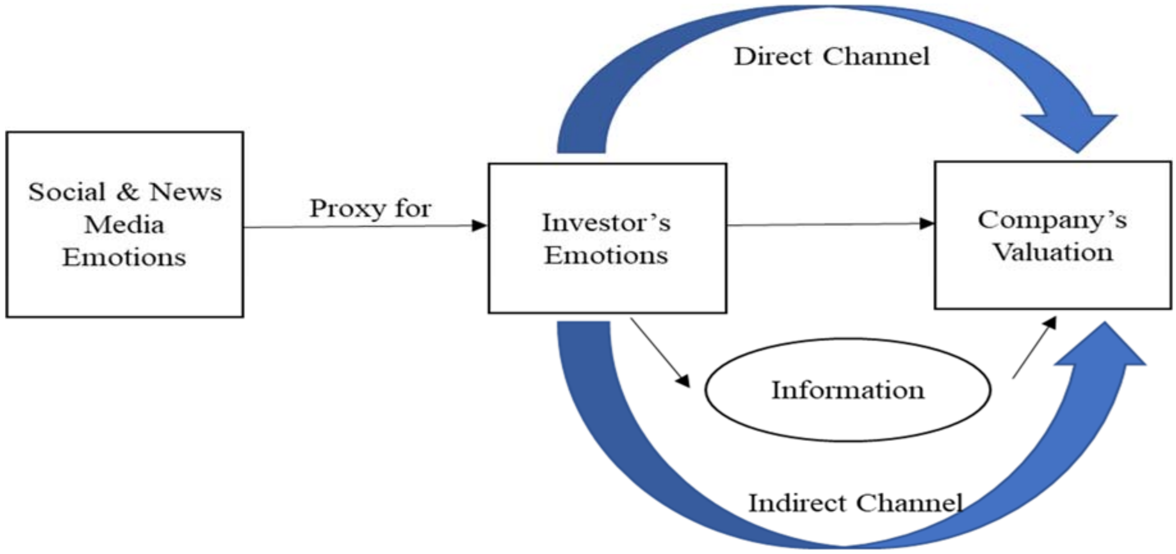


Table 1: Summary of Variables

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 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 2

Panel A			**Panel B**		
Regression Results of Unexpected Earnings			**Regression Results of Negative and Positive Unexpected Earnings**		
Variables	CAR (0, 1)		Variables	CAR (0, 1)	
			NUE	0.017	***
UE	0.024	***	PUE	0.034	***
Ln (MV)	-0.002	***	Ln (MV)	-0.002	***
BTM	0.019	***	BTM	0.018	***
Beta	0.002	**	Beta	0.001	
VIX	0.001	*	VIX	0.001	
FQ4	-0.001		FQ4	0.001	
Loss	-0.012	***	Loss	-0.014	***
Friday	-0.003	***	Friday	-0.003	***
Evol	0.000		Evol	-0.001	
Momentum	-0.071	***	Momentum	-0.071	***
Obs.	45,191		Obs.	45,191	
R-squared	0.037		R-squared	0.039	
Effects	Yes		Effects	Yes	
SE clustering	Yes		SE Clustering	Yes	

Table 2, Panel A reports the results for regression Eq..1

$CAR_{i,t} = \alpha + \beta_1 UE_{i,t} + \beta_2 Ln(MV)_{i,t} + \beta_3 Log(BTM)_{i,t} + \beta_4 Beta_{i,t} + \beta_5 FQ4_{i,t} + \beta_6 Loss_{i,t} + \beta_7 VIX_{i,t} + \beta_8 Friday_{i,t} + \beta_9 Evol_{i,t} + \beta_{10} MoM_{i,t} + FQ\ Effects + Sector\ Effects + \varepsilon_{i,t}$ … (Eq 1)

where $CAR_{i,t}$ is the cumulative abnormal return for firm "i" over the event window "t" (in our case, t = 0, 1). $UE_{i,t}$ are the unexpected earnings for firm "i" at time "t". 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. The control variables are defined in table 1. We have added the fiscal quarter effects to account for the heterogeneity in price reactions over time and sector effects to isolate within sector variations. OLS standard errors can be biased and may under or overestimate coefficient variability. To enhance robustness, we follow Petersen (2009) and cluster the standard errors by firms to account for potential correlation over time at the firm level. All subsequent equations include the specified control variables, fiscal quarter effects, sector effects, and standard error clustering by firms. *** p<0.01, ** p<0.05, * p<0.1.

Table 2 Panel B reports the results for regression Eq…2.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 2)

Several studies have shown that the magnitude of the investor response can differ between good news and bad news (e.g., Bird and Yeung, 2012; Williams, 2015). Therefore, we apply Equation 2 to our data to investigate the separate price impact of unexpected good news (PUE) and unexpected bad news (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 coefficients reported in panel B of table 2 for NUE (β_1=0.017***) and PUE (β_2=0.034***) 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 previous findings and perhaps reflects that unlike other studies, we confine our sample to only firms within the S&P500 index.

We further divide the Unexpected Earnings into Positive Unexpected Earnings (PUE) and Negative Unexpected Earnings (NUE).

Table 3: Impact of *Aggregate_Emotion* on Response to Earnings Announcements, Aggregate Positive Emotions and Aggregate Negative Emotions

Panel A: Impact of *Aggregate_Emotion* on Response to Earnings Announcements

		Social + News		Social Media		News Media	
NUE	Hi Agg.Emotion	0.012	**	0.022	***	0.012	**
	Lo Agg.Emotion	0.021	***	0.013	**	0.027	***
	Difference	-0.009		0.010		-0.015	
PUE	Hi Agg.Emotion	0.058	***	0.051	***	0.055	***
	Lo Agg.Emotion	0.008		0.016	***	0.011	*
	Difference	0.050	***	0.034	***	0.044	***
Company	FEt-1	0.114	***	0.046	***	0.123	***
	ΔFEt-1 to 1	0.166	***	0.085	***	0.176	***

Panel B: Aggregate Positive Emotions (optimism, joy, trust, and love/hate)

		Social + News		Social Media		News Media	
NUE	Hi Agg_positive	0.006		0.013	***	0.013	***
	Lo Agg_positive	0.024	***	0.021	***	0.025	***
	Difference	-0.017	**	-0.007		-0.012	
PUE	Hi Agg_positive	0.061	***	0.053	***	0.047	***
	Lo Agg_positive	0.016	***	0.020	***	0.026	***
	Difference	0.045	***	0.033	***	0.021	*
Company	FEt-1	0.122	***	0.050	***	0.139	***

	ΔFEt-1 to 1	0.165	***	0.073	***	0.192	***

Panel C: Aggregate Negative Emotions (stress, gloom, fear, anger, and conflict)

		Social + News		Social Media		News Media	
NUE	Hi Agg_negative	0.024	***	0.019	***	0.021	***
	Lo Agg_negative	0.014	***	0.017	***	0.015	***
	Difference	0.010		0.002		0.005	
PUE	Hi Agg_negative	0.022	***	0.023	***	0.018	***
	Lo Agg_negative	0.042	***	0.042	***	0.040	***
	Difference	-0.020	***	-0.019	**	-0.022	**
Company	FEt-1	-0.054	***	-0.015	*	-0.057	***
	ΔFEt-1 to 1	-0.098	***	-0.045	***	-0.084	***

Table 3 reports the results for the following regression.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t-1} + \beta_8 \Delta FEt_{i,t-1,1} + \sum\beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 3)

In addition to the annotation of table 2, 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). Panel A shows the results of Aggregate_Emotion where the value of R-Squared is 0.060 for Social+News, 0.051 for Social and 0.064 for News Media. Panel B shows the results of Aggregate Positive Emotions where the value of R-Squared is 0.056 for Social+News, 0.048 for Social and 0.059 for News Media. Panel C shows the results of Aggregate Positive Emotions where the value of R-Squared is 0.044 for Social+News, 0.042 for Social and 0.040 for News Media.

We perform a Wald-test to determine if the coefficients are statistically significant from zero. *** p<0.01, ** p<0.05, * p<0.1

Table 4: The Impact of the Emotions (Aggregate_Emotion) Over Time

		NUE					
	Media Source	01/98 – 12/05		01/06-06/13		07/13-12/17	
High - Low	Social and News	0.006		-0.006		-0.030	**
	Social	0.010		0.014		-0.014	
	News	0.039		-0.044	***	-0.017	
		PUE					
	Media Source	01/98 – 12/05		01/06-06/13		07/13-12/17	
High - Low	Social and News	0.038	**	0.053	***	0.052	***
	Social	0.039	**	0.032	**	0.029	
	News	0.023		0.058	***	0.043	***
		Direct Effect					
	Media Source	01/98 – 12/05		01/06-06/13		07/13-12/17	
Level	Social and News	0.062	***	0.141	***	0.120	***
	Social	0.020		0.040	***	0.080	***
	News	0.108	***	0.123	***	0.124	***
	Media Source						
Change	Social and News	0.110	***	0.192	***	0.182	***
	Social	0.048	***	0.086	***	0.129	***
	News	0.168	***	0.168	***	0.189	***

The above table reports the results for the following regression.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t} + \beta_8 \Delta FEt_{i,t-1,1} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 3)

In addition to the annotation for Table 3, 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.

Appendix 2: Impact of Positive Emotions on the Response to Earnings Announcements

			Social + News		Social Media		News Media	
Optimism	**NUE**	**Hi optimism**	0.008	*	0.012	***	0.020	***
		Lo optimism	0.021	***	0.021	***	0.012	***
		Difference	-0.014	**	-0.008		0.007	
	PUE	**Hi optimism**	0.051	***	0.055	***	0.048	***
		Lo optimism	0.018	***	0.016	***	0.019	***
		Difference	0.033	***	0.038	***	0.029	***
	Company	**FEt-1**	0.095	***	0.030	***	0.104	***
		ΔFEt-1 to 1	0.096	***	0.033	***	0.107	***
Joy			**Social + News**		**Social Media**		**News Media**	
	NUE	**Hi joy**	0.003		0.007		-0.003	
		Lo joy	0.028	***	0.028	***	0.034	***
		Difference	-0.025	***	-0.021	**	-0.036	***
	PUE	**Hi joy**	0.047	***	0.055	***	0.060	***
		Lo joy	0.032	***	0.025	***	0.023	***
		Difference	0.014		0.030	***	0.038	**
	Company	**FEt-1**	0.102	***	0.062	***	0.051	
		ΔFEt-1 to 1	0.097	***	0.067	***	0.048	
Trust			**Social + News**		**Social Media**		**News Media**	
	NUE	**Hi trust**	0.014	**	0.020	***	0.014	**
		Lo trust	0.021	***	0.017	***	0.027	***
		Difference	-0.007		0.002		-0.014	
	PUE	**Hi trust**	0.051	***	0.046	***	0.042	***
		Lo trust	0.023	***	0.028	***	0.031	***

		Difference	0.028	***	0.018	*	0.011	
	Company	**FEt-1**	0.312	***	0.142	***	0.319	***
		ΔFEt-1 to 1	0.331	***	0.155	***	0.347	***
Love/Hate			**Social + News**		**Social Media**		**News Media**	
	NUE	**Hi love/hate**	0.004		0.011	*	0.019	**
		Lo love/hate	0.025	***	0.022	***	0.020	***
		Difference	-0.020	**	-0.011		-0.001	
	PUE	**Hi love/hate**	0.048	***	0.063	***	0.047	***
		Lo love/hate	0.031	***	0.019	***	0.035	***
		Difference	0.017		0.044	***	0.012	
	Company	**FEt-1**	0.045	**	0.027	*	0.002	
		ΔFEt-1 to 1	0.045	**	0.045	***	-0.018	

The above table reports the results for the following regression.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t} + \beta_8 \Delta FEt_{i,t-1,1} + \sum \beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 3)

In addition to the annotation of table 3, the R-Squared value for different emotions ranges from 0.070 to 0.038.

Appendix 3: Impact of Negative Emotions on Response to Earnings Announcements

			Social + News		Social Media		News Media	
Stress	**NUE**	**Hi stress**	0.028	***	0.023	***	0.027	***
		Lo stress	0.010	***	0.014	***	0.012	***
		Difference	0.017	**	0.009		0.015	*
	PUE	**Hi stress**	0.017	***	0.025	***	0.020	***
		Lo stress	0.043	***	0.040	***	0.038	***
		Difference	-0.025	***	-0.015	*	-0.017	**
	Company	**FEt-1**	-0.144	***	-0.043	***	-0.121	***
		ΔFEt-1 to 1	-0.152	***	-0.053	***	-0.127	***
Gloom			**Social + News**		Social Media		News Media	
	NUE	**Hi gloom**	0.023	***	0.025	***	0.024	***
		Lo gloom	0.009	**	0.009	**	0.011	*
		Difference	0.015	**	0.016	*	0.014	
	PUE	**Hi gloom**	0.016	***	0.028	***	0.022	***
		Lo gloom	0.048	***	0.040	***	0.041	***
		Difference	-0.032	***	-0.012		-0.019	
	Company	**FEt-1**	-0.230	***	-0.061	***	-0.250	***
		ΔFEt-1 to 1	-0.247	***	-0.073	***	-0.267	***
Fear			**Social + News**		Social Media		News Media	
	NUE	**Hi fear**	0.026	***	0.024	***	0.017	**
		Lo fear	0.011	**	0.008		0.025	***
		Difference	0.015	*	0.016		-0.008	
	PUE	**Hi fear**	0.028	***	0.032	***	0.028	***
		Lo fear	0.041	***	0.040	***	0.041	***

		Difference	-0.013		-0.008		-0.014	
	Company	**FEt-1**	-0.022		0.014		-0.031	
		ΔFEt-1 to 1	-0.019		0.037	*	-0.042	
Anger			**Social + News**		Social Media		News Media	
	NUE	**Hi anger**	0.028	***	0.031	***	0.024	***
		Lo anger	0.013	***	0.012	**	0.024	***
		Difference	0.015		0.019	*	0.000	
	PUE	**Hi anger**	0.026	***	0.029	***	0.035	***
		Lo anger	0.041	***	0.038	***	0.045	***
		Difference	-0.015		-0.009		-0.009	
	Company	**FEt-1**	0.037		0.022		0.090	*
		ΔFEt-1 to 1	0.027		0.033	*	0.095	
Conflict			**Social + News**		Social Media		News Media	
	NUE	**Hi conflict**	0.018	***	0.017	***	0.018	***
		Lo conflict	0.016	***	0.017	***	0.019	***
		Difference	0.002		-0.001		-0.001	
	PUE	**Hi conflict**	0.023	***	0.027	***	0.030	***
		Lo conflict	0.046	***	0.046	***	0.036	***
		Difference	-0.023	**	-0.019	**	-0.006	
	Company	**FEt-1**	-0.025	***	-0.013	***	-0.018	**
		ΔFEt-1 to 1	-0.029	***	-0.017	***	-0.015	**

The above table reports the results for the following regression.

$CAR_{i,t} = \alpha + \beta_1 NUE_{i,t} + \beta_2 PUE_{i,t} + \beta_3 X_1 NUE_{i,t} + \beta_4 X_1 PUE_{i,t} + \beta_5 X_2 NUE_{i,t} + \beta_6 X_2 PUE_{i,t} + \beta_7 FEt_{i,t} + \beta_8 \Delta FEt_{i,t-1,1} + \sum\beta_k Control\ Variables + \Sigma Effects + \varepsilon_{i,t}$ … (Eq. 3)

In addition to the annotation of table 3, the R-Squared value for different emotions ranges from 0.052 to 0.037.

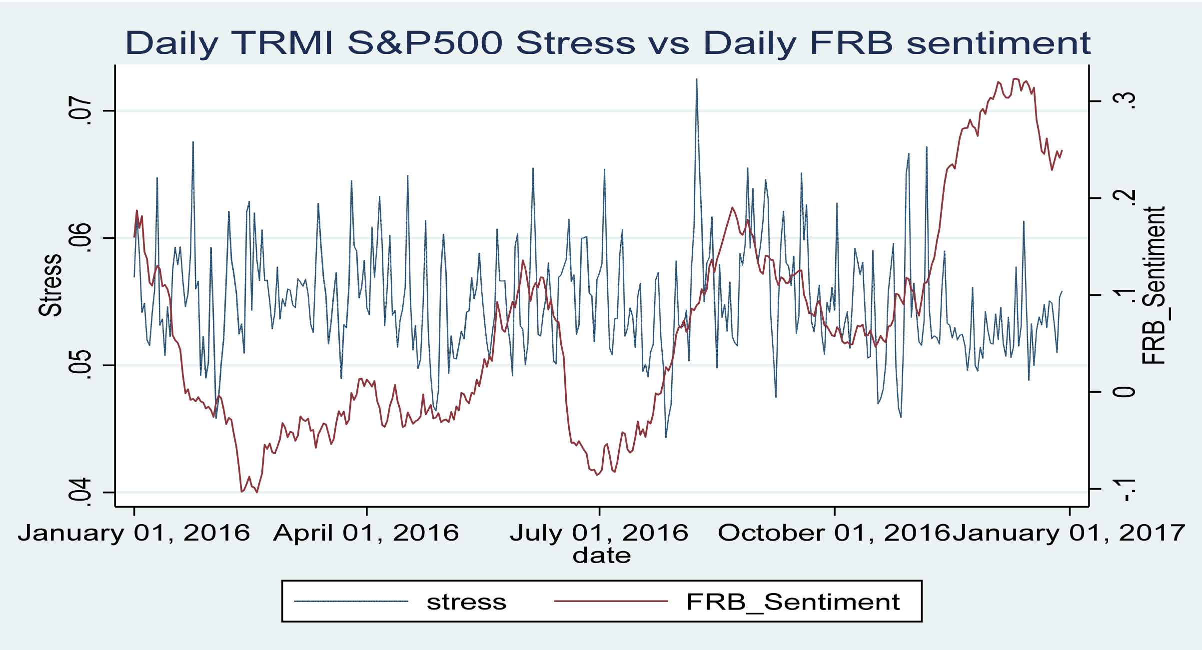
Appendix 1-

We use the comparison below to highlight the difference between sentiment and emotion.

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[17](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. (ii) If we look at the emotion of STRESS[18] 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 A1.1: 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).

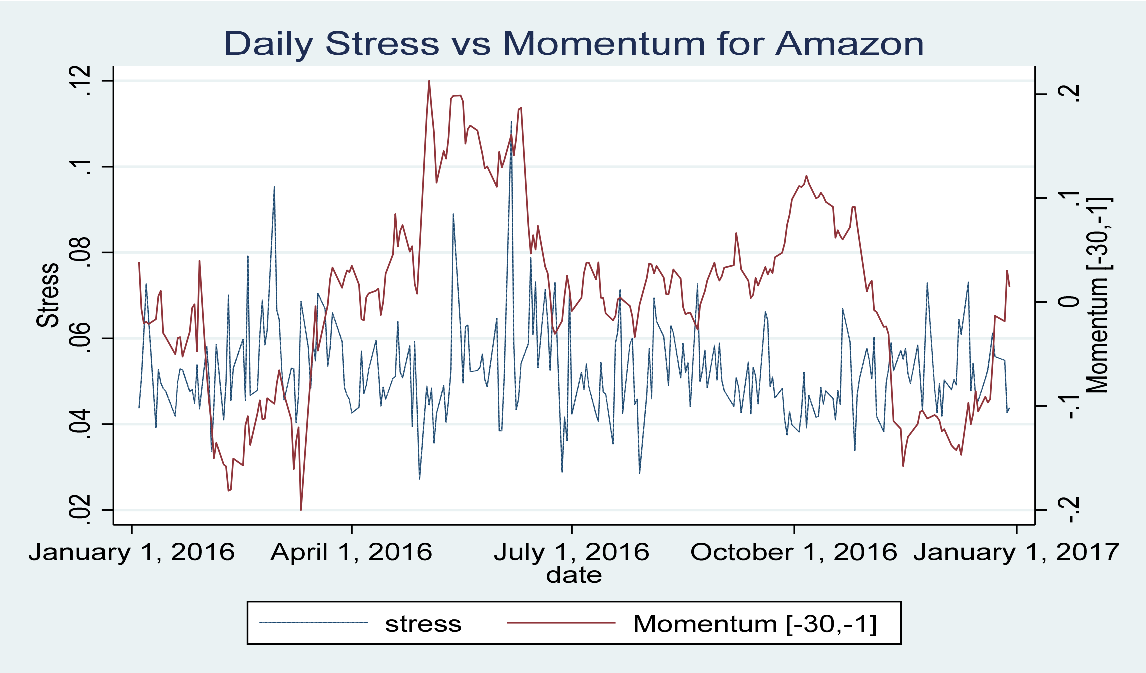


[17] https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/
18 We did the analysis for all the emotions with sentiment. The results of other emotions are quantitatively similar, and graphs would be available on request.

As figure A1.1 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 case[19]) sentiment is momentum (-30, -1) whereas the proxy for firm emotion is the TRMI emotion index. The results are similar to what we see in figure 1.1.

Figure A1.2: 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 emotions and sentiment, we calculated the correlations between our nine individual emotions measures and three aggregated emotions measures with the two daily sentiment scores. The first column in Table A1.1. reports these correlations calculated at the level of the S&P500 where the sentiment measure is the FRB sentiment score discussed above. The second set of correlations reported in the second column

19 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.

are calculated at the level of the individual stocks and use their momentum as the proxy for sentiment. The information provided clearly demonstrates` that the correlations between emotions and sentiment are very low with the largest correlation reported in the first column being 0.3873 for individual emotions and 0.4722 for aggregate emotions, and those reported in the second column being close to zero.

Table A1.1: Correlation between Emotions measures and Sentiment measures

Emotions	**FRB Sentiment**	**Momentum (-30, -1)**
Optimism	0.3873	0.0469
Joy	0.2228	0.0398
Lovehate	0.3523	0.0506
Trust	0.1782	0.0354
Stress	-0.3154	-0.0367
Gloom	-0.1092	-0.0275
Fear	-0.0529	0.0023
Conflict	0.0535	-0.0219
Anger	0.1146	-0.0015
Agg_Pos	0.4722	0.0674
Agg_Neg	-0.1229	-0.0345
Agg_Emotion	0.3510	0.0632