The Effect of Media Emotions on Asset Prices

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ABSTRACT

This paper replicates and extends the research performed by Garcia (2013). Using an extensive sample of financial columns from the *New York Times* and the *Wall Street Journal* between 1890 and 2015, the predictive effect of media emotions is tested on stock prices. As a proxy for each media emotion, the fraction of words representing that emotion in a column is used. The results show that general positive and negative affect help predict asset prices. A higher fraction of positive (negative) words in a financial column increases (decreases) the returns on the Dow Jones. Partial evidence is found that this effect is more pronounced during recessions than during expansions. Also, the emotion of serenity positively predicts stock returns. On the other hand, it is found that stock returns have a predictive effect on media emotions as well. Positive returns increase the fraction with which media content contains positive affect and the emotion of self-assurance, while negative returns similarly increase this fraction for negative affect and the emotions of fear and sadness. The main implication of this research is that investor sentiment limits market efficiency, providing additional support for the theoretical foundations of the behavioral finance paradigm.

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Contents

I. Introduction

The traditional finance paradigm and the standard economic models of decision-making that are derived from it describe investors to be rational, updating their beliefs correctly and making choices that are normatively acceptable. This should translate into financial markets to be efficient in the sense that asset prices fully reflect all available information and therefore correspond with their fundamental values. In recent years, however, behavioral economists have challenged the assumption of rationality and describe how agents fail to update their beliefs correctly or how individual decision-making is normatively questionable. The field of behavioral finance builds on two basic principles, namely investor sentiment and the limits to arbitrage that affect rationality in financial markets.

The effect of investor sentiment on financial markets has been researched by multiple studies. Tetlock (2007) finds that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and specifically high or low pessimism predicts high market trading volume. In addition, Garcia (2013) finds that the predictability of stock returns using emotion indices based on general positive and negative affect in financial news content is concentrated in recessions.

Based on the aforementioned findings, the goal of this research is to replicate and extend the work of Garcia (2013) in order to add to the existing body of knowledge in the literature. Replication is performed by using a similar sample period, dataset and the Loughran and McDonald (2011) dictionary to test the effect of general positive and negative affect on asset prices. Extension is performed by expanding the original sample period of Garcia with 25 years. In addition, the construction of eleven specific emotion indices based on the PANAS-X as conceptualized by Watson and Clark (1999) and subsequently testing their predictive effect on stock returns forms the main extension to the work of Garcia (2013).

The data sample in this research ranges from 1890 to 2015 and includes financial columns from the *New York Times* and the *Wall Street Journal*. Furthermore, the effect of media emotions is measured on the Dow Jones Industrial Average and the potential difference of effects between expansions and recessions is tested by using historical business cycle information from the National Bureau of Economic Research.

In line with the work of Garcia (2013), the main finding of this research regarding the emotion indices of general positive and negative affect as constructed by Loughran and McDonald (2011) suggests that these emotions indeed help predict stock returns. Specifically, a higher fraction of positive words in a financial column increases the returns on the Dow Jones, while a higher fraction of negative words similarly decreases these returns. Furthermore, the pessimism media variable, which is constructed by subtracting the positive from the negative emotion scale, shows a negative correlation with stock returns as well. It is furthermore found that this predictive effect is more consequential during recessions than during expansions for the pessimism scale. In addition, it is observed that the initial predictive effect of the positive and pessimism emotion scales partially reverses over the following trading days. Furthermore, partial evidence is found that the pessimism scale shows a Monday/ post-holiday effect, which is only present during recessions.

From the PANAS-X emotion scales, the results show that only the emotion of serenity significantly and positively predicts the following day's stock returns. It is furthermore found that, for most of the positive and negative emotion scales, the loadings of their correlations are in line with the hypothesized direction in the sense that a positive (negative) emotion would logically show a positive (negative) correlation with stock returns. Also, partial evidence is found that the emotion of sadness shows a significant Monday/ post-holiday effect.

Subsequently, after dividing the data sample into one subsample for the *New York Times* and one for the *Wall Street Journal*, it is found that more emotion scales significantly predict stock returns for the the *New York Times* sample. This applies to general positive and negative affect and the emotion of fear.

At the same time, it is found that stock returns have a predictive effect on media emotions as well. With regard to the Loughran and McDonald emotion scales, positive stock returns increase the fraction of positive words in news content while they similarly decrease this fraction for negative words. This effect is found to be significant during expansions as well as in recessions. Furthermore, no significant difference in predictive effect is found between both business cycles, which is in line with the results of Garcia (2013).

From the PANAS-X emotion indices, the emotions of self-assurance, fear and sadness are found to be influenced by stock prices as well. These emotions are all affected in the predicted direction; whereas the positive emotion scale of self-assurance is positively influenced by stock returns, the negative emotion scales of fear and sadness show a negative correlation. Furthermore, the results show that stock prices have a larger predictive effect on the degree to which news content contains the emotion of fear during expansions than during recessions, while this effect is more pronounced during recessions for the emotion of sadness.

The findings of this research contribute to the existing body of knowledge in the literature by not only investigating whether general positive and negative emotions have a predictive effect on asset prices, but also whether more specific emotions are determinants of stock return behavior. For practitioners, the findings of this research may be valuable as a potentially outperforming investment strategy can be constructed. Specifically, this can be done using firm-specific news and analyzing the reaction of different firms' stocks to positive and negative affect, the pessimism variable and the emotion of serenity. Subsequently, by ranking companies on their reported emotion scores on a continuous basis, taking a long position in stocks with high levels of positive affect and serenity, while going short on stocks with high levels of negative affect and the pessimism variable, could generate an investment strategy that outperforms the market. With regard to the aforementioned, the general implication that can be drawn from this research is that financial markets are not fully rational, offering more support for the notion that investor sentiment limits this rationality.

The remainder of this research is organized as follows. In Section II, the related literature is presented. In Section III, the procedure of data collection and the research methodology are described. In Section IV, the results are summarized. The paper is concluded in Section V.

II. Literature review

A. Efficient Market Hypothesis

The primary role of the capital market is to allocate the ownership of the economy's capital stock. The ideal in this regard would be that the market provides accurate signals for resource allocation, where firms make production-investment decisions and investors can choose among the securities that represent ownership of firms' activities under the assumption that security prices at any time fully reflect all information that is available. Market efficiency is reached when all prices fully reflect all available information and therefore always correspond with their fundamental values.

The aforementioned concept is known in financial literature as the Efficient Market Hypothesis (EMH). Since the EMH suggests that market prices should only react to new information and changes in discount rates, a main implication is that it is impossible to consistently outperform the market on a risk-adjusted basis. This would remove the possibility for investors to either purchase undervalued or sell overvalued stocks. Hence, the only way to obtain higher returns is either by chance or by attracting capital that involves a higher portion of risk (Fama, 1970).

B. Traditional finance

Barberis and Thaler (2003) describe the main idea of the traditional finance paradigm to be that investors are determined as 'rational'. This rationality has two implications. First, when agents receive new information, they update their beliefs correctly, in the way described by Bayes' law. Second, agents make choices that are normatively acceptable given their beliefs, in the sense that they correspond with Savage's notion of Subjective Expected Utility (SEU). Furthermore, the traditional finance model suggests, in correspondence with the EMH, that capital markets equal the rational present value of expected future cash flows.

C. *Behavioral finance*

Behavioral finance is a relatively new approach to financial markets that has partly emerged in response to the difficulties faced by the traditional finance paradigm. In general, this approach argues that some financial phenomena can better be understood using models in which agents are not fully rational. Models in behavioral finance either describe how agents fail to update their beliefs correctly, or show how individual decision-making is normatively questionable. In other words, the study of behavioral finance analyzes what happens when we relax one or both of the two aforementioned tenets that underlie individual rationality. In some behavioral finance models, agents fail to update their beliefs correctly. In other models, agents apply Bayes' law properly but make choices that are normatively questionable, in that they are incompatible with SEU (Barberis and Thaler, 2003).

More specifically, most traditional models of asset pricing use the Rational Expectations Equilibrium framework (REE), which not only assumes that individuals are rational but also that they have consistent beliefs (Sargent, 1993). Here, having consistent beliefs means that agents' beliefs are correct, in that the subjective distribution that is used to forecast future realizations of unknown variables is indeed the distribution that those realizations are drawn from. Apart from processing information correctly, this also requires agents to have enough information about the structure of the economy to be able to figure out the correct distribution for these variables. The violation of consistent beliefs is sometimes referred to as bounded rationality or structural uncertainty, with an example being that of investors that do not know the exact growth rate of an asset's cash flows but learn it as best as they can from the available data. Behavioral finance departs from the REE framework by either relaxing the assumption of individual rationality or by relaxing the consistent beliefs assumption (Barberis and Thaler, 2003).

Researchers in behavioral finance focus on two basic assumptions in order to augment the standard finance model. Firstly, it is argued that betting against sentimental investors is costly and risky. This causes rational investors, also known as arbitrageurs, to not act as aggressive in forcing prices to fundamentals as the standard finance model would suggest. This phenomenon is commonly described as the limits to arbitrage. Secondly, researchers in behavioral finance assume that investors are subject to sentiment, which is defined as a belief about future cash flows and investment risks that is not justified by the facts at hand (Baker and Wurgler, 2007).

C.1. Limits to arbitrage

Arbitrage is defined as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices" (Sharpe and Alexander, 1990). Textbook arbitrage requires no capital and entails no risk. However, in reality almost all arbitrage requires capital and is typically risky. This leads to the concept of limits to arbitrage, which argues that it can be difficult for rational traders to undo market inefficiencies by less rational traders.

Multiple studies have shown a certain degree of limits to arbitrage that is present in financial markets. Furthermore, it is shown that these limits occur in volatile arbitrage positions, which, although offering attractive average returns, expose arbitrageurs to risk of losses and the need to liquidate the portfolio under pressure from the investors in the fund (Shleifer and Vishny, 1997). Consistent with these findings, Ali, Hwang, and Trombley (2003) find that, among others, stocks' idiosyncratic return volatility is associated with a greater book-to-market effect.

In addition, Wurgler and Zhuravskaya (2002) argue that, while in textbook theory demand curves for stocks are kept flat by riskless arbitrage between perfect substitutes, in reality individual stocks do not have perfect substitutes, which results in a deterrence of risk-averse arbitrageurs from flattening these demand curves. Hence, arbitrage is weaker and mispricing is likely to be more consequential among stocks without close substitutes.

Also, Lamont and Thaler (2003) investigate the violations of the law of one price, a theory arguing that the same asset cannot trade simultaneously at different prices. They specifically study equity carve-outs followed by a spinoff of the remaining shares of the subsidiary company and find that, while holders of a share of parent company A are expected to receive x shares of subsidiary B, the price of A in reality turns out to be less than x times the price of B. Although this highlights a clear market inefficiency, arbitrage opportunities are eliminated due to shorting costs.

C.2. Sentiment

Investor sentiment is broadly defined as a belief about future cash flows and investment risks that is not justified by the facts at hand (Baker and Wurgler, 2007).

Previous research has shown multiple examples of how investor sentiment affects financial markets. In their paper, Barberis, Shleifer, and Vishny (1998) present a model of investor sentiment in which it is shown how people seem to overreact to high strength of evidence they are presented with, while they underreact to a similar high statistical weight of such news. In particular, the authors argue that their model is consistent with the conceptualized representativeness heuristic of Kahneman and Tversky (1972), where individuals view events as representative while ignoring the laws of probability, which causes overreaction. Also, the model relates to the psychological phenomenon of conservatism, described as the slow updating of models in the face of new evidence (Edwards, 1968), causing underreaction.

Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) attribute under- and overreaction to investor overconfidence and biased self-attribution. In addition, Burnside, Han, Hirshleifer, and Wang (2011) hypothesize overconfidence to explain the forward premium puzzle, which describes the difference between the forward and spot exchange rates to negatively forecast subsequent exchange rate changes. Specifically, investors would overreact to information about future inflation, causing the forward rate to grow proportionally more than the spot rate.

Furthermore, Hong and Stein (1999) contribute to the under- and overreaction theory by hypothesizing that any short-run underreaction to certain news must eventually lead to overreaction in the long run.

Also, Baker and Wurgler (2007) find that this sentiment has more structural impact on stocks that are difficult to arbitrage, such as small stocks and stocks for which relatively little information is available. They furthermore argue that, as individual investors may be more prone to sentiment, asset types regularly owned by this type of investors may also be more prone to mispricing.

D. Psychology

Behavioral finance suggests through its main assumptions of limits to arbitrage and sentiment that if irrational traders cause security prices to deviate from their fundamental values, arbitrageurs may be unable to correct mispricing. The structure of these deviations is generally assumed to be caused by people's structural biases that arise when forming beliefs and preferences. Hence, economists turn to the experimental evidence derived by cognitive psychologists when explaining concepts that deviate from the traditional finance paradigm (Barberis and Thaler, 2003).

D.1. Beliefs and preferences

Beliefs are described as internal informational representations of the relationship between actions and outcomes (Gintis, 2006). A specification of how agents generate expectations forms a crucial component of any model of financial markets. Similarly, forming assumptions about investors' preferences, or the way in which they evaluate risky gambles, is an essential component in understanding asset prices or trading behavior. Irrationality behind investor behavior is based on beliefs and preferences and shows in the form of behavioral biases (Barberis and Thaler, 2003).

Existing literature describes a number of biases with regard to beliefs that form the basis of irrationality. One example is that of overconfidence, which causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Also, optimism and wishful thinking cause people to display unrealistically rosy views of their abilities and prospects (Weinstein, 1980). Other biases in beliefs that have been employed in the literature are that of representativeness and conservatism. On one hand, it is found that individuals tend to rely too heavily on small samples, which causes them to view these as overly representative of the underlying population. On the other hand, individuals tend to rely too little on large samples, causing them to update their beliefs too conservatively (Coval and Shumway, 2005).

As aforementioned, classical economic models assume that investors evaluate gambles according to the Subjective Expected Utility framework. However, literature has employed a number of preference-based deviations from rationality that violate this. One of the most influential theories that tries to better capture how individuals' preferences are formed is that of prospect theory, which describes utility functions to be convex in the region of losses, kinked at zero, and concave in the region of gains. Specifically, prospect theory describes people to underweight outcomes that are merely probable in comparison with outcomes that are obtained with certainty. This is called the certainty effect, which makes individuals risk-averse in choices involving sure gains and risk seeking in choices involving sure losses. This makes the value function for losses generally steeper than for gains. Moreover, the isolation effect causes people to discard components that are shared by all prospects under consideration and leads to inconsistent preferences when the same choice is presented in different forms (Kahneman and Tversky, 1979).

Another widely accepted violation of the Subjective Expected Utility framework with regard to preferences is the concept of ambiguity aversion. This bias suggests that individuals dislike situations in which they are uncertain about the probability distribution of a gamble. The Subjective Expected Utility framework does not allow agents to express their degree of confidence with regard to probability distribution and are therefore unable to capture such aversion (Barberis and Thaler, 2003).

D.2. Effect of emotions on decision making

Beliefs and preferences are found to be influenced by emotions. Emotion is described as a mental state arising spontaneously rather than through the conscious effort and is often accompanied by physiological changes. A vast literature supports the idea that moods and emotions can considerably influence cognitive processes. First, it is shown that individuals are more likely to recall information from memory that is congruent rather than incongruent with their current feeling (Isen, Shalker, Clark, and Karp (1978); Bower (1981)). Second, individuals may use their apparent affective response to a target as a basis of judgment and they tend to be evaluating a target more positively when they are in a happy rather than in a sad mood. Furthermore, individuals that are in a happy mood tend to overestimate the likelihood of positive, while underestimating the likelihood of negative outcomes of events, whereas the opposite holds for those in a sad mood (Johnson and Tversky, 1983).

In addition, it is found that individuals' affective states influence the information processing strategy that is adopted. The concept of affect is closely related to emotion and is defined as the experience of feeling or emotion. Individuals that are in a happy mood are more likely to adopt a heuristic processing strategy that is characterized by top-down processing, with high reliance on pre-existing knowledge structures, while relatively little attention is paid to the details of the situation at hand. Conversely, individuals that are in a sad mood more likely adopt a systematic processing strategy that entails a bottom-up processing method, with little reliance on pre-existing knowledge structures, while relatively much attention is paid to the details of the situation at hand (Schwarz and Clore, 1996).

As affect influences the information processing strategy, it subsequently affects decision making as well. Tiedens and Linton (2001) argue that there is a difference between emotions characterized by certainty or uncertainty. They state that certainty associated with an emotion affects the certainty experienced in situations and find that emotions associated with certainty result in greater reliance on the expertise of a source, more stereotyping and less attention to the quality of an argument compared with emotions associated with uncertainty. Furthermore, Gino, Wood, and Schweitzer (2012) show that anxiety makes agents more receptive to advice, even if this advice is bad.

The field of behavioral economics extends the effect of emotions on decision making to financial decisions and therefore financial markets as a whole. Knutson, Wimmer, Kuhnen, and Winkielman (2008) find that positive and arousing emotional states induce people to take more risk and to be more confident when evaluating available investment options, relative to neutral states, while negative emotions have the opposite effects.

Affect can be generated either endogenously by outcomes of prior actions, or by exogenous manipulations, for which the focus of this research lies on the latter. For example, Hirshleifer and Shumway (2003) show that the amount of sunshine is strongly correlated with stock returns. They state that returns increase as the amount of sunshine in a day also increases. The basic idea behind this is that sunny weather is associated with positive emotions. Furthermore, Edmans, Garcia, and Norli (2007) investigate the reaction of financial markets to sudden changes in investor mood. Specifically, they use international football results as a mood variable, since evidence exists that there is a strong link between football outcomes and mood. The researchers find that there is a significant market decline after football losses, indicating that negative emotions have a negative impact on stock returns.

D.3. PANAS-X

Throughout previous research, two general factors, namely positive and negative affect, have consistently emerged in studies of affective structures. They appear to be the first two factors in factor analyses of self-rated mood and as the first two dimensions in multidimensional scalings of mood terms or facial expressions. The terms positive and negative affect strongly suggest that the two represent opposite emotions and have emerged as two highly distinctive dimensions.

Positive affect (PA) is described as the extent to which an individual feels enthusiastic, active and alert, and high PA is a state of high energy, full concentration and pleasurable engagement, whereas low PA is normally reflected in sadness and lethargy. Conversely, negative affect (NA) is a general dimension of subjective distress and unpleasant engagement that generally shows in the form of a number of aversive mood states, including anger, contempt, disgust, guilt, fear and nervousness, with low NA representing a state of calmness and serenity (Watson, Clark, and Tellegen, 1988).

With the two aforementioned affective states as the basis, Watson et al. (1988) have developed and validated measures of positive and negative affect. The result of these measures is defined as the PANAS (Positive and Negative Affect Schedule). The goal in developing the PANAS scales has been to create reliable and valid measures and therefore the primary focus has been to select descriptors that were relative pure markers of either positive or negative affect. As an extension to this schedule, Watson and Clark (1999) have developed a number of specific affect scales, which together form an affect schedule that is also known as the PANAS-X.

The PANAS-X comprises three basic positive emotion scales, four basic negative emotion scales and four other affective state scales. For positive affect, these scales comprise the emotions of joviality, self-assurance and attentiveness. For negative affect, the basic emotion scales are represented by the emotions of fear, hostility, guilt and sadness. The other affective states are the emotions of shyness, fatigue, serenity and surprise. Each of the scales is composed of a number of 'items', which are key identifiers for each specific emotion. The PANAS-X scales and their item composition are summarized in Table I in the Appendix.

E. Media and financial markets

Mass media have a strong influence on public opinion. McCombs and Shaw (1972) argue that editors, newsroom staff and broadcasters play an important role in shaping political reality when choosing and displaying news. Apart from obtaining new information, readers are taught how much importance to attach to a piece of information based on the amount of information included and the position of the text.

Multiple studies have researched the effect of media sentiment on financial markets. Huberman and Regev (2001) test whether enthusiastic public media attention has an effect on asset prices. They study the specific case of a pharmaceutical company and the potential development of its new cancercuring drugs and find that media (over)enthusiasm can actually cause a permanent rise in share prices, even though no genuinely new information is presented.

Furthermore, by researching the effects of investor sentiment on stock returns, Baker and Wurgler (2007) find that sentiment can actually predict asset prices. In particular, they find that the effect of sentiment differs on a cross-sectional level, being especially high for low capitalization, younger, unprofitable, high volatility, non-dividend paying, growth, and financial distress stocks.

Also, Tetlock (2007) researches the role of media in the stock market and finds that high media pessimism predicts downward pressures on market prices, which are followed by a reversion to fundamentals. Secondly, specifically high or low values of media pessimism forecast high market trading volume. Thirdly, low market returns lead to high media pessimism.

The more recent work of Garcia (2013) studies the effect of sentiment on asset prices during a sample period from 1905 to 2005. In this research, financial columns from the *New York Times* and the *Wall Street Journal* have been collected and their contents are used to analyze the fraction of positive and negative words to proxy for media sentiment. The most important result is that media sentiment predicts stock returns. Particularly, Garcia finds that an increasing ratio of positive words in media content generates higher returns, and an increasing ratio of negative words in media content generates lower returns. Furthermore, he finds that the predictive effect of sentiment is highest during recessions. Another finding is that asset prices have a feedback effect on media sentiment, which means that the asset prices can predict whether the sentiment will be positive or negative. Furthermore, media content varies more within than across business cycles. The media sentiment predictive effect appears to be higher on Mondays and after holidays, and particularly high ratios of positive or negative words in the columns make trading volumes peak. Finally, no predictability is found in the intraday returns after the opening of the stock market.

F. Hypotheses

This research is based on that of Garcia (2013), in which his work is partly replicated and largely extended. Replication takes place by researching the predictive effect of media sentiment on asset prices among a similar sample and a similar period. However, his research is extended by not only testing whether positive and negative words in general have a predictive effect, but also whether the PANAS-X affect scales have a predictive effect on asset prices. Furthermore, Garcia's original sample period is extended and covers the period from 1890 to 2015.

Firstly, it is examined whether media emotions, which comprise both positive sentiment, negative sentiment and the PANAS-X affect scales, predict asset prices. This hypothesis is tested using three sub-hypotheses. In line with the research of Garcia (2013), it is expected that a higher percentage of positive words in a column generates higher returns, while a higher percentage of negative words generates lower returns. Therefore, the assumption is made that the basic positive emotion scales in the PANAS-X as constructed by Watson and Clark (1999) will generate similar higher returns, while the opposite holds for the basic negative emotion scales. Furthermore, as Garcia finds that the predictive effect of media sentiment is higher during recessions than in expansions, the same is expected for the media emotions tested in this research. Lastly, as Garcia finds, it is expected that the predictive effect is highest on days after the last closing day of the market. This finding is supported by the notion that newspapers have significantly higher circulation during the weekends and holidays, since investors have more time to read them (DellaVigna and Pollet, 2009). The first hypothesis and its sub-hypotheses are summarized as follows:

Hypothesis 1: *Media emotions predict asset prices.*

Hypothesis 1.1: *An increasing ratio of positive (negative) emotions in media content generates higher (lower) returns.*

Hypothesis 1.2: *The predictive effect of media emotions is higher during recessions than in expansions.*

Hypothesis 1.3: *The predictive effect of media emotions is higher for Mondays and post-holiday days than for other days of the week.*

To test the robustness of the results, an additional hypothesis is formed to research whether the effect of emotions on the DJIA is different between the *New York Times* sample and that of the *Wall Street Journal*:

Hypothesis 2: *The degree to which media emotions predict asset prices does not vary between New York Times and Wall Street Journal columns.*

Furthermore, Garcia (2013) finds that asset prices have a feedback effect on media content and sentiment. This feedback effect shows to be similar during expansions and recessions. Therefore, it is expected in this research that the feedback effect on media emotions does not vary between expansions and recessions. The third hypothesis and its sub-hypothesis are summarized as follows:

Hypothesis 3: *Asset prices have a feedback effect on media emotions.*

Hypothesis 3.1: *The feedback effect of asset prices does not vary between expansions and recessions.*

III. Data and methodology

A. Data

Following Garcia (2013), three sources of data are used in order to replicate and extend existing research. These sources consist of stock return information, business cycle information and a number of media emotion indices.

Firstly, the stock returns of the Dow Jones Industrial Average (DJIA) are collected from MeasuringWorth (Williamson, 2016), a website that makes historical data on economic aggregates available to the public. The DJIA was composed of twelve securities during the start of the sample period in 1890, which increased to twenty in 1916 and reached the amount of thirty in 1928, from which point it has been stable up to this moment. Its composition, however, has changed over the years (Garcia, 2013). Furthermore, R_t denotes the log return on the DJIA index on date t.

Secondly, business cycle information is obtained from the National Bureau of Economic Research (NBER) website, a leading economic research organization dedicated to conducting economic research. One of its areas of research comprises the examination of business cycles, where it considers recessions to start at the peak of a business cycle and end at the trough, causing expansions to logically start at the trough and end at the peak. [1]

Thirdly, the media content analysis is performed using data from the *New York Times* and the *Wall Street Journal* article archive. This data has been retrieved from three databases, namely LexisNexis, Factiva and ProQuest.

In order to replicate Garcia (2013), the data sample between the period of 1905-2005 comprises a number of identical columns that generate a consistent dataset covering financial news on a daily basis. From the archive of the *New York Times*, these concern the columns "Financial Markets" and "Topics in Wall Street". The "Topics in Wall Street" column has been published under several different names during the sample period (namely "Market Place" and "Sidelights"). From the *Wall Street Journal*, the column "Abreast of the Market" was used.

The extension to the sample of Garcia (2013), for the period of 2006-2015, comprises the "Abreast of the Market" column from the *Wall Street Journal*. From the *New York Times*, the column "Stocks and Bonds" and the blogs "Dealbook" and "Economix" were used. In addition, this research extends that of Garcia with a collection of columns for the period between of 1890-1904. From the *New York Times*, this includes articles from the "Financial Markets" and "Topics in Wall Street" columns. From the *Wall Street Journal*, articles from "Comment on the Market", "Early Morning Matter" and "The Monetary Situation" were collected. These columns contain, similar to those used by Garcia, a consistent set of articles that have been published on a daily basis between 1890 and 1904.

In total, the complete data sample covers a period of 126 years (from 1890 to 2015) and includes 85,570 data files. Figure 1 presents a sample of "Topics

[1] See http://www.measuringworth.org/DJA/ for the data from Williamson (2016). See http://www.nber.org/cycles.html for the data from NBER.

in Wall Street" and "Abreast of the Market", respectively, of which the majority of the total data sample is composed. In total, 57,520 articles are from the *New York Times*, whereas 28,050 are from the *Wall Street Journal*. Table II in the Appendix gives an overview of the columns used in the sample.

Data collection from each of the aforementioned databases results in downloaded PDF files. For most of the articles in the data sample, these PDF files concern images, photocopied from a physical newspaper. To construct the media emotion scales, it is necessary to transform the scanned images into readable documents and subsequently export them into plain text files. This is done using "Optimal Character Recognition" (OCR). Specifically, the same methods are used as Garcia (2013) has by making use of ABBYY FineReader,[2] which is considered as the leading software package in OCR processing. Not all text is perfectly recognized by the OCR software due to limited quality of the original scanned image, causing typographical errors in the data sample. This adds random noise to the media emotion scales and therefore does not bias the conclusions of this research.

Following Garcia (2013), the amount of positive and negative words is derived from each column using the categorization dictionary of Loughran and McDonald (2011). This dictionary contains a total of 2,355 negative and 354 positive words that take into account the nuances of finance jargon and thus yields particular merits for processing articles on financial events.

In addition to the aforementioned general dimension scales of negative and positive affect, Watson and Clark (1999) are followed to construct eleven more specific emotion indices. Specifically, the PANAS-X scales as elaborated on in Section II.D.3 are used and emotion indices of the three basic positive emotion scales (joviality, self-assurance and attentiveness), the four basic negative emotion scales (fear, hostility, guilt and sadness) and the four other affective states (shyness, fatigue, serenity and surprise) are constructed. For each defined term belonging to each emotion, synonyms have been generated using Thesaurus.[3] Subsequently, each word has been examined thor-

[2]See https://www.abbyy.com/en-eu/finereader/ for more information about ABBYY FineReader

[3]See https://http://www.thesaurus.com/ for more information about Thesaurus

oughly on its unambiguous meaning and suitability in a financial context, after which all of its conjugations have been added to their specific emotion index.

Analysis of the articles was done using MAXQDA.[4] After the sample of columns and the aforementioned emotion indices have been imported into it, this program is able to scan each of the text files and give an output that summarizes the total amount of words and the amount of words belonging to each emotion index for every individual column in the sample.

Tables III, IV, V and VI in the Appendix present the sample statistics for each of the emotion scales used in this research. The sample ranges from 1890 to 2015 and includes a total of 34,458 trading days, for which 32,438 trading days include at least one financial news column. This leaves a total of of 2,020 trading days for which no column has been found. The largest part of missing articles falls in the period between 1890 and 1904, due to a relatively lower consistency in financial columns that were published on a daily base in these years.

Table III summarizes the Loughran and McDonald (2011) emotion scales and Panel A indicates that, over the entire period, an average amount of positive and negative words is present in each article that equals 0.98% and 1.87%, respectively. The standard deviation for the positive emotion scale is 0.45% and equals 0.86% for the negative variant. Subsequently, the mean of the pessimism scale equals that of the negative minus the positive emotion scale and results in 0.88%, with a standard deviation of 0.86%. Breaking down the sample into business cycles, Panels B and C subdivide the data sample into recessions and expansions, respectively. As can be concluded from these statistics, the average amount of positive words decreases slightly during recessions, and increases during expansions (0.96% versus 0.99%). The average amount of negative words shows to be somewhat lower during recessions than in expansionary periods (1.77% versus 1.90%).

Table IV shows the average amount of words per article as a fraction of the total amount of words for the emotions of joviality, self-assurance and

[4]See http://www.maxqda.com/ for more information about MAXQDA

attentiveness, which are 0.039%, 0.090% and 0.009%, respectively. Furthermore, the average fraction of words indicating the emotions of self-assurance and attentiveness shows to be higher for expansions (0.094% > 0.078% and 0.009% > 0.008%), while

With regard to the PANAS-X negative emotion scales, Table V shows that the emotions of fear, hostility, guilt and sadness represent an average fraction per article of 0.124%, 0.013% and 0.010% and 0.026% respectively. Furthermore, Panels B and C show that the emotions of fear, hostility and guilt occur relatively more often during expansionary periods (0.129% > 0.111%, 0.0.013% > 0.012% and 0.010% > 0.009%), while sadness occurs more often during recessions (0.035% > 0.023%).

Table VI shows that the PANAS-X other affective state scales of shyness, fatigue, serenity and surprise represent 0.001%, 0.006%, 0.005% and 0.019%, respectively. Panels B and C show that the emotions of shyness and serenity occur more often during recessions than during expansions (0.006% > 0.001% and 0.006% > 0.004%). Furthermore, the fraction of words representing the emotion of fatigue occurs more often during expansions (0.007% > 0.005%) while the emotion of surprise does not seem to change between recessions and expansions.

In summary, one can conclude that the mean score for the amount of words that represent each PANAS-X emotion in an article is considerably lower than that for the aforementioned general emotion scales as constructed by Loughran and McDonald (2011). This is a logical consequence, since each of the constructed PANAS-X scales comprises less words than the Loughran and McDonald dictionaries.

B. Methodology

The emotion scales are constructed by dating them to day t, on which an article was written, keeping in mind that they are published in the morning of day $t+1$. The rationale behind this is that information in an article belongs to date t. This supports the essence of this research, which tries to combine all the collected news written and printed before the market opened, and then examines whether the content can predict the following day's stock returns. Furthermore, w_{it} denotes the total number of words in an article.

To define the emotion scales, the notion of consecutive and non-consecutive trading days has to be taken into account, which is in line with the work of Garcia (2013). For consecutive trading days when the market is open on both day t and $t+1$, the general dimension scales of the emotions examined in this research are postulated as $\chi_t = \sum_i x_{it} / \sum_i w_{it}$, with χ representing the amount of words that belongs to a specific emotion as a percentage of the total amount of words in each article. Furthermore, it is assumed that columns published during non-consecutive trading days contain information belonging to the last trading day. For this reason, a differentiation between consecutive and non-consecutive trading days has to be made. The specification for non-consecutive trading days is postulated as $\chi_t = \sum_{i,s=t}^{s=t+h} x_{is} / \sum_{i,s=t}^{s=t+h} w_{sh}$. Here, h denotes the number of days the market has been closed before that specific non-consecutive market day. For each of the additional emotion scales as constructed by Watson and Clark (1999), the same approach has been used.

According to Garcia (2013) and Tetlock (2007), it is unclear to what extent emotion scales may lag stock returns. Therefore, the emotion variables contain lagged coefficients to indicate whether the shock to stock returns caused by media content is permanent or temporary. Furthermore, the emotion scales are always normalized so they have zero mean and unit variance, which allows for the interpretation of the regression coefficients in terms of one standard deviation shocks to the emotion scales. This simplifies the interpretation of the economic magnitude of the results. Also, White (1980) heteroskedasticity-robust standard errors are reported in each specification.

B.1. Stock returns during expansions and recessions

To determine stock returns, the following model is estimated:

$$R_t = (1 - D_t)\gamma_1 L_s(R_t) + D_t \gamma_2 L_s(R_t) + \eta X_t + \epsilon_t, \tag{1}$$

The dependent variable R_t is the log-return on the DJIA from 1890 to

2015. L_s denotes a lag operator with $s = 5$. The variable D_t is a dummy variable that has the value 1 if date t is during a recession and 0 when it belongs to an expansion. Furthermore, the vector X_t concerns a set of exogenous variables, including a constant term, 'day-of-the-week' dummy and a dummy variable for whether date t is during a recession or an expansion. Also, ϵ_t is a zero-mean error term with possibly time-varying volatility.

Table VII in the Appendix gives summary statistics on the DJIA returns. Panel A shows that, on average, the mean return on the DJIA during the total sample period of 1890 to 2015 was 1.7 basis points per day. During expansions, comprising 25,463 days out of the total 34,458 trading days in the sample, the average return was 4 basis points. With regard to recessionary periods, comprising 8,995 days, the average DJIA return was –4.6 basis points. Furthermore, the daily volatility of stock returns during recessions is considerably higher than that during expansions, with 140 compared to 94 basis points. Panel B presents the estimates of a parsimonious time-series model, which is specified in 1. The last three rows in this panel suggest that there is a Monday effect in the sample. Specifically, the returns on Mondays are, on average, 11 to 15 basis points lower than during the other days of the week.

Some parts of the analysis include a GARCH(1,1) model that is fitted to the returns of the DJIA to account for time-varying volatility in the sample. Specifically, a model will be estimated with a constant mean, $R_t = \mu + \epsilon_t$, and time-varying volatility $\sigma^2_{t+1} = \omega + \alpha_1 \epsilon^2_t + \beta_1 \sigma^2_t$, where $\sigma^2_t \equiv \text{var}(\epsilon_t)$. The estimated coefficients for the variance equation are given in Panel C of Table VII.

B.2. Stock returns and emotion scales

To study the relationship between stock returns on the DJIA and the constructed emotion scales, the same models have been used as constructed by Garcia (2013). The basic model to test this relationship is as follows:

$$R_t = \beta L_s(M_t) + \gamma L_s(R_t) + \psi(R^2_t) + \eta X_t + \epsilon_t. \tag{2}$$

Here, M_t denotes one of the emotion scales. The coefficient β presents the point estimates for each of the emotion scales. A formal F-test is conducted to examine whether the parameters of the one period lagged emotion scale variables are statistically significant from zero. Furthermore, it is tested whether the sum of the lagged variables' coefficients from period two to five is different from zero.

B.3. Stock returns and emotion scales along the business cycle

To differentiate the effect of news content on stock returns along the business cycle, the following model is tested:

$$\begin{aligned} R_t =& (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) \\ &+ D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t. \end{aligned} \tag{3}$$

In this model, the coefficients β_1 and β_2 measure the effect of media content on stock returns during expansions and recessions, respectively. An F-test is conducted in order to examine whether the effects of media content on stock returns is different during expansions than during recessions. This is firstly done by testing whether the parameters of the one period lagged emotion scales significantly differ between expansions and recessions, and secondly by testing whether the sum of the lagged variables' coefficients from period two to five are different from zero for both expansions and recessions.

B.4. Stock returns on Mondays and post-holiday days

To test whether the effect of the emotion scales on stock returns is stronger on Mondays and post-holiday days compared to that of days during the week, the following specification is defined:

$$\begin{aligned} R_t =& (1-I_t)[(1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1(R_t^2)) + D_t(\beta_3 L_s(M_t) \\ &+ \gamma_3 L_s(R_t) + \psi_3(R_t^2))] + (1-I_t)[(1-D_t)(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) \\ &+ \psi_2(R_t^2)) + D_t(\beta_4 L_s(M_t) + \gamma_4 L_s(R_t) + \psi_4(R_t^2))] + \eta X_t + \epsilon_t. \end{aligned} \tag{4}$$

Here, an indicator variable I_t is defined that takes the value one if and only if the previous day is not a trading day (i.e., Mondays or post-holiday days). Furthermore, the coefficients β_1 and β_2 measure the effect of media content on stock returns for Mondays/ post-holiday days and back-to-back weekdays during expansions, respectively. Conversely, β_3 and β_4 measure the effect of media content on stock returns for Mondays/ post-holiday days and back-to-back weekdays during recessions, respectively. To check whether the difference between the coefficients is significantly different from zero, an F-test is conducted.

B.5. Robustness checks

For the emotion scales that have shown the most reliable correlations with the daily DJIA returns, the results from Equation 3 are further tested on their reliability. This is done by re-running the specification in three different ways. Firstly, the log returns are substituted with a normalization of the log returns through the GARCH(1,1) time-varying volatility model. Here, the estimated daily volatility from the model is constructed with σ_t, which leads to a normalization of the returns of the DJIA, specified as R_t/σ_t. The normalization constructs a time-series of stock returns with its volatility normalized to unity. Secondly, the emotion scales are orthogonalized, in which they represent the residual from specification 3. This is done in order to strip the emotion scales metrics off any linear relationship with returns. Thirdly, a robust regression based on the M-estimator of Huber (1981) is used in order to deal with outliers.

Another robustness check is performed to investigate whether the effect of the emotion scales in media content is similar across the columns belonging to the *New York Times* and those from the *Wall Street Journal*. In order to test this, specification 3 is re-run on the two subsamples.

B.6. Information versus sentiment

In his research, Garcia (2013) posits the idea that the information that is present in media content may actually be novel instead of reflecting a summary of what happened earlier in financial markets, which would mean that the constructed emotion scales rather contain new information instead of measuring sentiment. Therefore, the possibility that not sentiment but actual new information could drive the results is tested. To analyze this, the hypothesis whether stock returns have an effect on media sentiment is tested with the following model:

$$\begin{aligned} M_t =& (1-D_t)(\lambda_1 R_t + \beta_1 L_s(R_t) + \gamma_1 L_s(M_t)) \\ &+ D_t(\lambda_2 R_t + \beta_2 L_s(R_t) + \gamma_2 L_s(M_t)) + \eta X_t + \upsilon_t. \end{aligned} \tag{5}$$

To test this model, both the log returns and normalized log returns using the GARCH(1,1) model are used. Furthermore, a formal F-test is conducted to check whether the parameters of the one period lagged emotion scale variables are statistically different from zero.

IV. Results

A. Feedback from emotion scales to the DJIA

Table VIII in the Appendix presents the results for the specification given in Equation 2 and tests the predictive effect of the Loughran and McDonald emotion scales on the DJIA. In general, the amount of positive and negative words as a fraction of the total amount of words in a column can help predict the stock returns of the following day. Specifically, it is shown that a one standard deviation shock to the positive, negative and pessimism metrics moves the conditional average return on the following day's DJIA by 6.9, –2.4 and –4.6 basis points, respectively. Furthermore, the coefficients of the lagged emotion scales from $t-2$ to $t-5$ indicate whether this initial shock to stock returns caused by the media content is permanent or temporary. For the positive emotion scale, the effect is temporary, since the lags for $t-2$ to $t-5$ are all negative. For the negative and pessimism emotion scales a similar reversal can be observed, for which the effect shows from $t-4$ and $t-3$, respectively. Panel B formally conducts a test whether the sum of the aforementioned coefficients $t-2$ to $t-5$ is different from zero. These show to be significantly different from zero for the positive and pessimism scale, providing more support for the notion that the effect is temporary. However, the statistical power is not as high as the test on some of the single coefficients.

Tables IX, X and XI re-run the same specification given in Equation 2 and similarly test the degree to which each of the emotion scales belonging to the PANAS-X can individually predict the following day's returns on the DJIA. Two out of the three positive emotion scales in Table IX, namely self-assurance and attentiveness, show an expected positive loading with regard to their effect on stock returns. Surprisingly, the emotion of joviality seems to negatively but not significantly predict the DJIA. While the results indicate that none of the three scales affects the DJIA with statistical significance, it is worth mentioning that the emotion of self-assurance shows to be the most consistent with regard to predictability (t=1.7).

Out of the four PANAS-X negative emotion scales in Table X, two show loadings on $t-1$ that are not in line with the hypotheses. Specifically, hostility and guilt seem to positively correlate with the next day's returns. However, their t-values show no statistical significance. Although not statistically significant either, the emotions of fear and sadness do show results for which their loadings on $t-1$ are as expected and for which their statistical significance shows to be considerably higher than that for the other two emotions (with t=–1.7 and t=–1.9, respectively).

For the PANAS-X other affective state scales as summarized in Table XI, the loadings of their effect on the DJIA on beforehand was unclear since these emotions do not necessarily represent positive or negative affect. As can be concluded, shyness, fatigue and surprise are inadequate predictors of returns since all three emotions have statistically insignificant t-values. Serenity, on the other hand, seems to positively correlate with the next day's DJIA, with a positive t-value of 2.7. The formal F-test in Panel B furthermore supports the notion that the predictive effect of the serenity emotion scale is different from zero (p=0.007).

Although the results are not presented, it should be noted that a multiple regression analysis has been performed in which Equation 2 is re-run on all

PANAS-X scales. By adding all emotions in one model and controlling for the possible influence that other media emotions can have, the predictive effect of each scale is tested. This, however, does not result in any significant other results than those found earlier in this section.

B. Feedback from emotion scales to the DJIA along the business cycle

Table XII presents the results for the specification given in Equation 3 and tests the predictive effect of the Loughran and McDonald emotion scales on the DJIA along the business cycle. In Panel A, the coefficient estimates of β_1 are summarized, which describe the effect that media emotions have on stock returns during expansions. The results show that the positive and pessimism emotion scales show predictability with statistical significance (t=3.4 and t=–3.1, respectively) with regard to their effect on stock returns. Here, a one standard deviation change leads to a positively correlated change in the DJIA of 5.4 basis points for the positive emotion scale, while the pessimism emotion scale shows a negative correlation of –2.7 basis points. Negative affect does not show any statistically significant predictability.

Panel B summarizes the coefficient estimates of β_2, describing the effect of media emotions on stock returns during recessions. The results show that, again, the positive and pessimism emotion scales show a predictive effect on stock returns that is statistically significant (t=2.5 and t=–3.2, respectively). A one standard deviation of the positive scale leads to a positively correlated change in the DJIA of 9.5 basis points, whereas the pessimism scale is negatively correlated with the DJIA, resulting in a negative change on stock returns of –8.5 basis points. Again, negative affect does not have statistically significant predictive power.

When comparing the effect of the emotion scales between Panel A and B, it can be concluded that their impact is more consequential during recessions than during expansions. The correlation almost doubles for the positive emotion scale and more or less triples for the negative and pessimism variables. The results showing that the magnitude of the effect is larger during recessions are in line with earlier findings of Tetlock (2007) and Garcia (2013).

However, the formal F-tests in Panel C support the notion that the effect between expansions and recessions is significantly different only for the pessimism scale (p=0.040).

The second and third rows in Panel C conduct formal F-tests to research whether the initial shock to the DJIA returns is of temporary or permanent nature for both expansions and recessions. As can be concluded, only the pessimism variable shows a statistically significant reversal between $t-2$ and $t-5$ that is present during expansions (p=0.010). This effect is not present during recessions and therefore the null hypothesis that there is no reversal cannot be rejected. This indicates that for recessionary periods, the initial effect of pessimism in media content is of permanent nature.

Tables XIII, XIV and XV re-run the same specification given in Equation 3 and similarly test the degree to which each of the emotion scales belonging to the PANAS-X can individually predict the following day's returns on the DJIA along the business cycle. Table XIII shows that the joviality scale is negatively and statistically insignificantly correlated with stock returns for both expansions and recessions. This is in line with the results from Table IX. Attentiveness shows to be positively correlated with stock returns during expansions but has a negative correlation with the DJIA during recessions. For both business cycles, the results are insignificant. Self-assurance shows to be positively correlated with stock returns during both expansions and recessions. Although the results are not significant for any of the business cycles, it can be observed that the effects of this emotion are more consequential during expansions than during recessions, with a one standard deviation shock resulting in an 11 basis points increase during expansions compared to an 8.9 basis points increase during recessions.

Table XIV summarizes the PANAS-X negative emotion scales and shows that, in line with the findings in Table X, the emotions of hostility and guilt have statistically insignificant predictive power on stock returns. The emotions of fear and sadness show a relatively higher level of significance and negative correlations with the DJIA returns for both expansionary and recessionary periods. As can be observed, both emotions show a higher level of significance during expansions than in recessions. A one standard deviation shock to fear decreases the subsequent stock returns by –9.3 basis points (t=–1.8) during expansions, while it decreases them by only –5.1 basis points during recessions (t=–0.3), making the effect more consequential during expansions than in recessions. A one standard deviation shock to the sadness metric results in a decrease in stock returns by –25.9 basis points during expansions (t=–1.5), while it decreases them by –36 basis points during recessions (t=–1.1), which shows that the effects of this emotion are more consequential during recessions. Furthermore, Panel C shows that for the emotion of sadness, its initial effect is temporary during expansions (p=0.026).

The results for the PANAS-X other affective state scales are summarized in Table XV and show that, similar to the earlier findings as summarized in Table XI, the emotions of shyness, fatigue and surprise do not show any statistically significant correlations with stock returns. Serenity shows to be positively correlated with the DJIA returns, but only significantly during expansions (with t=2.1 during expansions versus t=1.7 during recessions). Here, a one standard deviation shock to the serenity metric increases the following day's stock returns by 84.1 basis points, on average. On the other hand, the results from the first column of Panel C do not confirm the notion that the predictive effect of the emotion of serenity significantly differs between expansions and recessions. Furthermore, each of the four emotions tested shows to have more predictive power during expansions than during recessions, as their t-values are all higher for this business cycle. Also, the results do not show any significant reversal of effects that emotions have on stock returns after day $t-1$.

Similar to the previous section, a multiple regression analysis has been performed in which Equation 3 is re-run on all PANAS-X scales. However, controlling for the possible influence of other media emotions, the results do not yield any significant results that differ from those found earlier in this section.

C. *Feedback from emotion scales to the DJIA on Mondays and post-holiday days*

Subsequently, the sample is divided based on whether the previous day was a trading day or not. This way, it is examined whether media emotions have a different effect on stock returns on Mondays and post-holiday days compared to other days of the week. Tables XVI and XVII present the results for the specification given in Equation 4 and test the predictive effect of the emotion scales that have shown the most significant and consistent correlations with the DJIA in Sections IV.A and IV.B.

Table XVI summarizes the results for the Loughran and McDonald emotion scales. It can be observed that positive affect shows a somewhat higher correlation with the DJIA on Mondays and post-holiday days during recessions. However, this effect is not significant, both looking at its t-value and the F-test that cannot reject the null hypothesis that coefficients β_{31} and β_{41} are equal. Also, only the back-to-back weekdays show a significant correlation with stock returns for positive affect. The negative emotion scale does not show any significant support for a Monday or holiday effect either. The pessimism emotion scale shows a statistically significant predictive effect for Mondays and post-holiday days, which is only present during recessions (t=–2.5). Specifically, during recessions, a one standard deviation shock to the pessimism factor results in a decline on the DJIA of -10.4 basis points, compared to –8.7 basis points during regular weekdays. However, when looking at the formal F-tests to see whether this effect is different for recessions than during expansions or whether it differs from normal weekdays during recessions, no significant results are found. Therefore, only limited support is offered for the notion that the pessimism emotion scale shows a Monday or holiday effect, which is present only during recessions.

Table XVII summarizes the feedback effect of the self-assurance, fear, sadness and serenity emotion scales. As can be observed, only the emotion of sadness shows a significant Monday/ holiday effect when looking at the leading coefficients of β. Here, the effects are significant for both Mondays/ holidays during expansions and recessions (with t=–2.3 and t=–2.1, respectively). This effect shows to be more consequential during recessions than in expansionary periods, with a one standard deviation change to the sadness scale changing the DJIA by –96.4 basis points in recessions, compared to –87.3 basis points during expansions. However, the F-tests show that this effect is not significantly different from that during normal weekdays, offering only limited support.

The coefficients of β for the emotion of serenity seem to show an opposite effect; the correlation with the DJIA for normal weekdays is statistically significant and seems to be stronger than that during Mondays or post-holiday days, which shows for both expansions and recessions (with t=2.4 and t=3.0, respectively. This effect seems to be more consequential during recessions than in expansions, with a one standard deviation change of the serenity metric increasing the DJIA by 203 basis points, while only increasing it by 103 basis points during expansions. Again, the F-tests do not support for the findings in the first four rows of the table.

D. Robustness checks

D.1. Volatility adjustments, orthogonal emotion scales and robust regressions

Tables XVIII and XIX present a number of robustness checks with the aim to enforce previous results that have been found in Sections IV.A and IV.B for the Loughran and McDonald emotion scales and the PANAS-X emotion scales that have shown to have the highest levels of significance and consistence. As the analyses performed in earlier sections do not take time-varying volatility into account, a GARCH(1,1) model is used, for which the estimates of the terms are summarized in table VII. Robustness of earlier results is furthermore tested with orthogonalized emotion scales and a robust regression.

Panel A in Table XVIII presents the results from Equation 3 using the unit-variance DJIA index returns for the Loughran and McDonald emotion scales. The results indicate that the positive emotion scale positively and significantly predicts stock returns, but only during expansions. Also, the pessimism variable negatively and significantly influences stock returns, both during expansions as well as during recessions. The formal F-tests do not show a significant difference of effects between expansions and recessions for any of the three emotion scales. Panel B subsequently controls for autocorrelation and presents the results when the emotion scales are stripped off any possible day-of-the-week effects, linear relationships with returns and lags with orthogonal emotion scales. As can be concluded, each of the emotion scales has a more consequential effect on the DJIA returns during recessionary periods than during expansions. This is in line with earlier findings in Table XII. However, the F-tests do not support the notion that the effects significantly differ among both business cycles. Furthermore, the estimation in Panel C presents the results using a robust linear regression based on the M-estimator of Huber (1981), which allows for investigation whether outliers could be driving earlier results. Again, it can be observed that each emotion scale correlates to a higher degree with the DJIA during recessions when compared to expansions. For this reason, it can be concluded that the results are not driven by outliers. Similar to the results in Panel B, the formal F-tests in Panel C do not report a significant difference between the effects during expansions and recessions.

Table XIX presents the results of the robustness tests for the PANAS-X emotion scales of self-assurance, fear, sadness and serenity, respectively. In line with earlier results, the emotion scale of self-assurance for each of the panels shows to positively correlate with the DJIA returns. The emotion of fear shows to unexpectedly correlate positively with stock returns during recessions for each of the panels. For this reason, the robustness of earlier results in which fear negatively correlates with the DJIA returns during recessions can be questioned. Sadness keeps its negative correlation with the DJIA returns in all three panels and does so with statistical significance for the robust regression in Panel C for both expansions and recessions. Furthermore, the emotion of serenity in all three panels positively correlates with stock returns, which is in line with earlier findings. Also, the formal F-tests in each panel do not support any evidence for a significant difference in correlations between expansions and recessions or a reversal of an initial effect for any of the emotion scales tested.

D.2. Feedback from emotion scales to the DJIA along the business cycle - subsamples

To test whether the results found earlier are similar among the two sample subsets of *New York Times* and *Wall Street Journal* columns that were used for this research, Equation 3 is re-run on both groups. The results are summarized in Tables XX and XXI, which respectively test the effects for the Loughran and McDonald emotion scales and the PANAS-X scales for the emotions of self-assurance, fear, sadness and serenity.

Table XX presents the results for the predictive effect of the Loughran and McDonald emotion scales on the DJIA along the business cycle and Panels A and B show the effects for the *New York Times* subsample. As can be concluded, the positive emotion scale only significantly predicts stock returns during recessions, while the negative emotion scale does this for expansions only. The pessimism variable shows statistically significant correlations for both expansions and recessions and, in line with previous findings, the effects of the positive and pessimism variable are more consequential during recessions than in expansions. This is not the case for the negative emotion scale. The positive emotion scale furthermore shows a surprising negative loading on the DJIA during expansions. However, this effect is not significant.

Panels C and D summarize the effects for the *Wall Street Journal* subsample. As can be observed, only the positive emotion scale shows a statistically significant correlation with the DJIA returns, which is only present during recessions. The negative emotion scale does not show any significant correlations with stock prices and even shows a surprising positive loading on stock returns during recessions. Furthermore, the pessimism variable does not significantly influence the DJIA either and its effect seems to be more consequential during expansions. One can conclude that the *New York Times* subsample gives a better representation of the results found in previous analyses.

Table XXI subsequently presents the results for the predictive effect of the

PANAS-X emotion scales of self-assurance, fear, sadness and serenity, respectively. Panels A and B summarize the estimates for the *New York Times* subsamples. The positive correlations of self-assurance that were found in Table XIII seem to partly disappear, since, although not significantly, the loading of this emotion on the DJIA is negative for expansions. Only the emotion scale of fear shows a significant negative correlation with the DJIA returns, which is only present during expansions. Furthermore, sadness and serenity do not show any significant effects. Also, the loadings on the DJIA of the fear, sadness and serenity emotion scales on both expansions and recessions are all in line with previous results.

Panels C and D subsequently summarize the effects for the *Wall Street Journal* subsample and show that none of the emotion scales can significantly predict the DJIA returns. It can furthermore be observed that only the emotion scales of self-assurance and serenity show positive loadings on the DJIA during both expansions and recessions that are in line with previous findings. The fear and sadness scales seem to surprisingly correlate positively with stock returns during recessions, which is not in line with previous findings.

E. Feedback from stock prices to news content

When news content is affected as a consequence of stock prices, stronger support is offered for the notion that not new information, but actually sentiment is driving content and therefore also the emotions expressed in media content. Tables XXII and XXIII summarize the results for Equation 5 that tests the feedback effect from stock prices to news content. Again, it is observed whether the effects differ between expansions and recessions, since a difference in reporting style would be an indication of media processing information asymmetrically during both business cycles. In both tables, Panel B checks the robustness of the effects found in Panel A through a GARCH(1,1) model.

Table XXII presents the estimates of the predictive effect that the DJIA returns have on each of the Loughran and McDonald emotion scales. In line with the sentiment hypothesis, all three of the emotion scales are significantly predicted by stock returns. Here, positive stock returns increase the amount of positive and decrease the number of negative words in media content, which subsequently decreases the pessimism scale. As Table VII summarizes, the daily standard deviation of the DJIA during expansions is 94 basis points during expansions and 140 basis points during recessions. To illustrate, a one standard deviation increase in stock returns increases the percentage of positive words in the articles written that day during expansions by 0.1 standard deviations, while it only increases this amount by 0.05 standard deviations during recessions. This suggests that the feedback effect from stock prices to news content is stronger during expansions than during recessions. A similar pattern is found for the negative and pessimism emotion scales and the formal F-tests for the effect that the DJIA returns have on all three emotions can reject the hypothesis that the feedback effect from stock prices to news content is similar during both business cycles ($\lambda_1 = \lambda_2$). However, the results from Panel A should be conditioned by the fact that the volatility of stock returns is significantly higher during recessions than during expansions. Therefore, Panel B summarizes the estimates fitted with a GARCH(1,1) model, for which the terms are summarized in Table VII to deal with this time-varying volatility. As the formal F-tests reflect, stock returns do not show to have a significantly different effect on any of the three emotion scales during expansions than during recessions. This implies that the effect of a one standard deviation movement in stock returns on the emotion scales can be considered to be identical during both business cycles. This is in line with the findings of Garcia (2013).

Table XXIII subsequently presents the estimates of the DJIA returns' predictive effect on the PANAS-X emotion scales of self-assurance, fear, sadness and serenity, respectively. From Panel A, it can be concluded that stock returns significantly predict the degree to which news content is written with the emotions of self-assurance, fear and sadness. Stock returns significantly predict these emotion scales for both expansionary and recessionary periods. These emotions are all affected in the predicted direction; whereas the positive emotion scale of self-assurance is positively influenced by returns, the negative emotion scales of fear and sadness show a negative correlation. Only the emotion of serenity is not significantly affected by the DJIA returns. Again, it seems that the degree to which the significantly correlated emotion scales are affected is higher during expansionary than during recessionary periods. This intuition is supported by the formal F-test for the emotions of self-assurance and fear, but not for the sadness emotion scale. The GARCH(1,1) model in Panel B again corrects for time-varying volatility and the F-test can reject the hypothesis that the feedback effect from stock returns to the emotion scales is equal along the business cycle for the emotions of fear and sadness. Specifically, the results show that stock prices have a significantly larger predictive effect on the degree to which news content contains the emotion of fear during expansions than during recessions (as λ_1=–0.00017 and λ_2=–0.00009), while this effect on the emotion scale of sadness is more pronounced during recessions (as λ_2=–0.00003 and λ_1–0.00001).

V. Conclusion

A. Discussion

The main goal of this research has been to replicate and extend the work of Garcia (2013). Replication was performed by using a similar sample period, dataset and the Loughran and McDonald (2011) dictionary to test the effect of general positive and negative affect on asset prices. An addition to Garcia's original sample period of 25 years and the construction of eleven specific emotion indices based on the PANAS-X as conceptualized by Watson and Clark (1999) form the main extension to the work of Garcia (2013).

With regard to the first hypothesis of this research, it can be concluded that a number of media emotions predict asset prices. In line with the findings of Garcia (2013), it is found that the general positive and negative emotion scales as constructed by Loughran and McDonald (2011) indeed help predict stock returns. Specifically, a higher fraction of positive words in a financial column increases the returns on the Dow Jones, while a higher fraction of negative words similarly decreases these returns. The pessimism scale shows a negative correlation with stock returns as well. It is furthermore found that this predictive effect is more consequential during recessions than during expansions. In addition, it is observed that the initial predictive effect of news with regard to the positive and pessimism emotion scales partially reverses over the following trading days between t–2 to t–5, which argues for a non-informational impact (Garcia, 2013). Lastly, partial evidence is found that the pessimism scale shows a Monday/ post-holiday effect, which is only present during recessions.

The findings that support the results of Garcia (2013) and show that the predictive effect of the Loughran and McDonald emotion scales on asset prices is more consequential during recessions than during expansions offers support for the idea that media content proxies for investor sentiment. Specifically, if journalists produce informative signals for traders, it is unclear why the precision of these signals would increase during recessionary periods. This is because during economic downturns, the press is affected as both subscriptions and advertising revenues are highly pro-cyclical. It is unlikely that better coverage of financial markets is accompanied by the inevitable staff cuts as a result of decreased revenues.

From the PANAS-X emotion scales, only the emotion of serenity significantly and positively predicts the following day's stock returns. It is furthermore found that, for most of the positive and negative emotion scales, the loadings of their correlations are in line with the hypothesized direction. Specifically, from the three positive emotion scales, the emotions of self-assurance and attentiveness show positive correlations with stock returns, whereas from the four negative emotion scales, the emotions of fear and sadness show a negative correlation.

The PANAS-X emotion scales' predictive effect on the DJIA is not particularly more consequential during recessions than during expansions. Looking at the emotion scales that have shown the most significant and consistent results, namely that of self-assurance, fear, sadness and serenity, it can be concluded that each shows a more significant correlation during expansionary periods when compared to recessions while the strength of correlations differ. This implies that the effect for these emotions is not necessarily more pronounced during a specific business cycle, but has more explanatory power during expansions.

From the PANAS-X emotion scales of self-assurance, fear, sadness and serenity, limited support is found that the emotion of sadness shows a significant Monday/ post-holiday effect during both business cycles, which is more consequential during recessions than in expansions. Furthermore, no strong evidence for emotions having a stronger predictive effect on stock returns on such days is found.

The fact that both the Loughran and McDonald and, apart from that of sadness, all PANAS-X emotion scales show no significant difference between the returns on Mondays and post-holiday days, can be observed as a robustness check. As new information may have been included in financial columns by journalists while the markets were closed, it could be the case that the data in this research contains such information. Confirming that the predictive effect of media emotions on asset prices for practically all emotions tested does not differ between Mondays/ post-holiday days and back-to-back weekdays therefore offers more support for a reaction based on sentiment instead of new information.

Whereas the emotion scales of general positive and negative affect as constructed by Loughran and McDonald (2011) help predict stock returns, only little evidence is found that the emotion scales based on the PANAS-X as defined by Watson and Clark (1999) do so as well. This evokes a number of questions relating to both the quality of the constructed word lists of each PANAS-X emotion and the actual ability for each of the emotions to predict asset prices. With regard to the quality of the emotion lists, one could question whether these emotion lists as constructed are complete and contain no words for which their meaning could be ambiguous or even completely different in certain settings. On the other hand, it could also be the case that certain words are missing and, if included, could have led to a higher level of predictability. Although for each defined term comprising a PANAS-X emotion a thorough examination based on unambiguousness and suitability in a financial context has been performed, the subjectivity of this method cannot exclude the possibility for incomplete or incorrect words.

The second question referring to each of the PANAS-X emotion's potential to predict asset prices concerns whether these emotions are actually relevant in financial contexts. More specifically, one could question how relevant an emotion of, say, attentiveness, guilt or shyness is to test its effect on asset prices and therefore to what degree investors are actually influenced when these emotions occur relatively more often in financial columns.

As discussed, the emotions of self-assurance, fear, sadness and serenity have shown the most significant and consistent results throughout this research. The Oxford English Dictionary defines the emotion of self-assurance as the "feeling of security as to oneself" and "self-confidence" and the emotion of serenity as "cheerful tranquility". With regard to self-assurance, it was clear on beforehand that this emotion would logically have a positive effect on stock returns. This research shows that, to a certain degree, the presence of the emotion of serenity in media content has a positive positive effect on investors as well. The fact these emotions show relatively consistent positive correlations with stock returns therefore offers support for the idea that they are associated with a higher level of risk tolerance.

On the other hand, fear is defined as "the emotion of pain or uneasiness caused by the sense of impending danger, or by the prospect of some possible evil", while sadness is defined as "gravity of mind or demeanor". As these emotions are negatively correlated with the DJIA returns, the results suggest that investors are influenced by these emotions in media content and could subsequently withdraw their investments in financial markets (Simpson and Weiner, 1989).

With regard to the second main hypothesis of this research, the results provide additional insights. For the Loughran and McDonald emotion scales, the *New York Times* subsample shows significant results for the positive and negative emotion scales during recessions only and for the pessimism scale during both expansions and recessions. The *Wall Street Journal* only shows one significant correlation, which is for the positive emotion scale during recessions. This suggests that the degree to which the Loughran and McDonald media emotions predict asset prices is higher for the *New York Times* subsample.

From the PANAS-X emotion scales of self-assurance, fear, sadness and serenity, the only newspaper that shows a statistically significant correlation concerns the *New York Times* where the emotion of fear negatively predicts stock returns. This is only the case during expansions.

It should be noted that neither of the two subsamples provides a consistent set of results that is in line with earlier findings in this research or the previous results from works such as that of Tetlock (2007) or Garcia (2013). Specifically, both newspapers independently fail to consistently show that a higher ratio of positive (negative) emotions generates higher (lower) stock returns or that there is a higher correlation between stock returns and asset prices during recessions.

However, the notion that the *New York Times* shows significant correlations with stock returns for more emotion scales than the *Wall Street Journal* subsample leaves space for discussion. Whereas the *New York Times* publishes news of all kinds, the *Wall Street Journal* is a business-focused newspaper. This could offer arguments for a sentimental story in which asset prices are rather affected by emotions instead of by new information, especially in the *New York Times*. Specifically, as the audience of the *Wall Street Journal* primarily concerns investors or at least individuals with an affinity for financial markets, this group may be less prone to be influenced by media emotions than the average reader of the *New York Times*. As the sample in this research consists for about two thirds of *New York Times* columns, the results are primarily driven by this subsample. An interesting direction for further research would therefore be to examine whether the type of audience affects the predictive effect of media emotions.

To test the third hypothesis whether asset prices similarly have a predictive effect on the degree to which emotions are present in financial media, again the Loughran and McDonald and the four PANAS-X emotions of self-assurance, fear, sadness and serenity have been used. For the Loughran and McDonald emotion scales, it is found that stock returns are indeed important predictors for the fraction with which these emotions occur in financial columns. Here, positive stock returns increase the fraction of positive words in news content while they similarly decrease this fraction for negative words, which subsequently decreases the pessimism scale. This effect is found to be significant during expansions as well as in recessions. Furthermore, no significant difference in predictive effect is found between both business cycles. These results are in line with that of Garcia (2013).

With regard to the PANAS-X emotion scales, stock returns significantly predict the degree to which news content is written for the emotions of self-assurance, fear and sadness and do so for expansionary as well as recessionary periods. These emotions are all affected in the predicted direction; whereas the positive emotion scale of self-assurance is positively influenced by returns, the negative emotion scales of fear and sadness show a negative correlation. Furthermore, the results show that stock prices have a significantly larger predictive effect on the degree to which news content contains the emotion of fear during expansions than during recessions, while this effect on the emotion scale of sadness is more pronounced during recessions.

The significant feedback effect that asset prices have on most of the emotion scales tested gives more support for the notion that the results are not driven by new information, but rather by sentiment that is reflected in the degree to which authors use emotions in their financial columns. Specifically, journalists "tag along" to a certain degree, in the sense that their words are predictable given the previous day's stock returns. As emotions are predicted by these returns, more support for the idea that media content is rather driven by sentiment than possessing new information is offered.

This research adds additional insights to the body of existing literature and specifically shows that investor sentiment limits market efficiency. Based on the outcomes of this study, an investment strategy could be constructed. This strategy consists of analyzing media emotions and taking positions in the DJIA according to these results, where stocks for which relatively high levels of positive affect and serenity is present in its news content should be bought and stocks with similar levels of negative affect and the pessimism variable should be sold. As the results suggest that general positive affect and the pessimism variable show a reversal to fundamentals after their initial predictive effect on stock returns between $t-2$ and $t-5$, these positions have to be altered in a timely manner. This would lead to high transaction costs and may therefore result in an unprofitable trading strategy.

However, if the methods of this research are followed, but instead of using general financial columns, firm-specific news is analyzed, an alternative trading strategy could be constructed. Specifically, one could analyze the extent to which specific stocks react to each of the emotion scales that have shown to significantly predict asset prices and subsequently rank companies on their reported emotion scores on a continuous basis. Next, taking a long position in stocks with high levels of positive affect and serenity, while going short on stocks with high levels of negative affect and the pessimism variable, could generate an investment strategy that outperforms the market. This method is based on the research of Zhang and Skiena (2010), in which a trading strategy is constructed to exploit blog and news sentiment by ranking individual companies on their reported sentiment each day and subsequently going long on companies with high levels of positive news sentiment, while going short on similar stocks with high levels of negative sentiment. This strategy yields consistently favorable returns with low volatility over a long period.

With regard to the results discussed in this section, the general implication that can be drawn from this research is that financial markets are affected by investor sentiment, which limits their level of efficiency.

B. Limitations and future research

This research has a number of limitations that generally apply to the data sample and the constructed emotion indices. With regard to the data sample, a first possible limitation could be its representativeness. As has been mentioned in Section V.A, it could be the case that a different audience reacts differently to media emotions. Secondly, this research does not use an identical dataset as that of Garcia (2013), as it contains an additional set of columns from years not used in his research, but also uses different columns during his sample period. Also, a number of dates in this research' sample period, especially between the periods of 1890-1904 and 2006-2015, is not accompanied with financial columns. This could lead to different results. Thirdly, not all articles in the dataset were downloaded correctly. In rare cases, it occurred that opening text files would result in incomplete columns in which only the title or a few paragraphs were included.

The first limitation with regard to the constructed emotion indices used in this research is based on the actual completeness and correctness of these indices. As each index was constructed based on personal intuition, the possibility for subjectivity cannot be eliminated. Secondly, this basic technique of qualitative data analysis based on single words may not capture the exact essence expressed in financial columns. These limitations address the possibility that the emotion scales as tested in this research are incomplete and do not reflect the full potential of an emotion to predict stock returns.

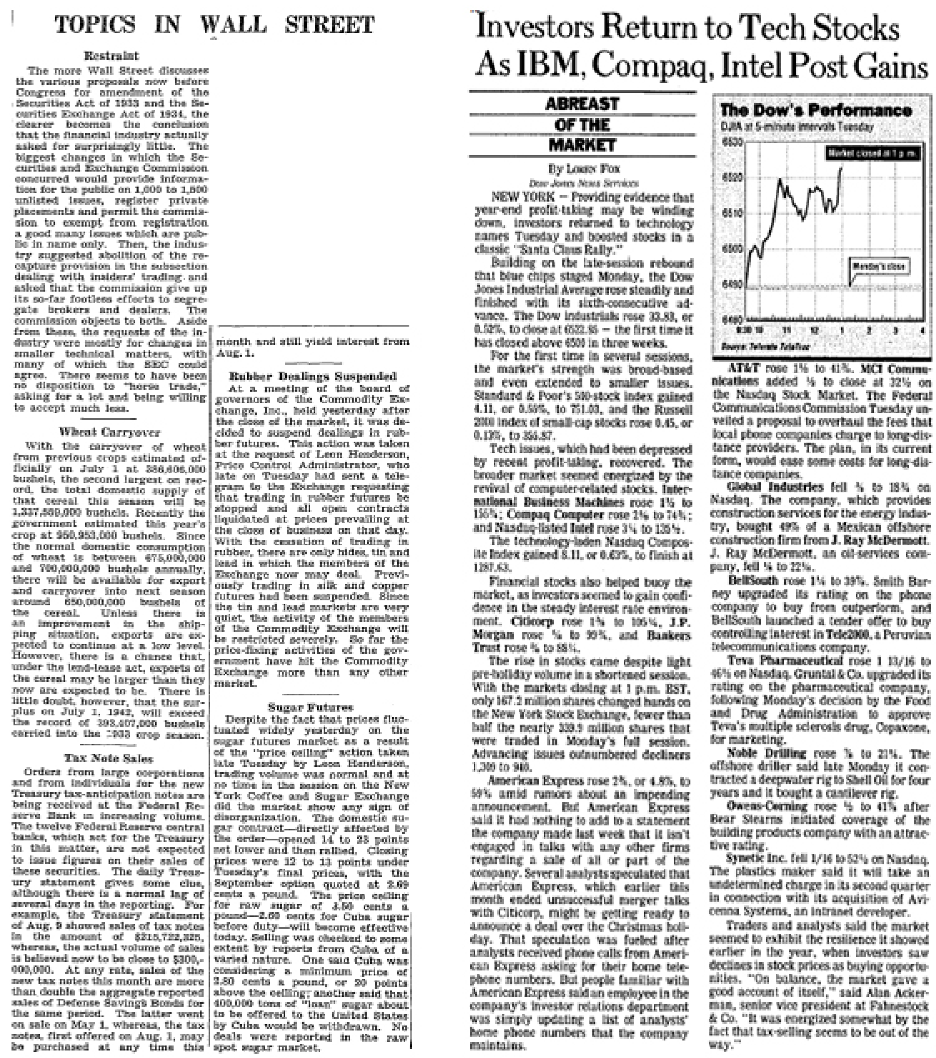
The aforementioned limitations and the general implications of this research offer a number of directions for future research. To address the limitation with regard to the representativeness of the data sample, an interesting area for future research would be to investigate the effect of media emotions on different types of audiences. Here, a valuable addition could be to correct for factors such as the amount of daily readers or the page number on which a column was written. Secondly, future research could focus on capturing media emotions with more advanced techniques of qualitative data analysis, in which the essence of media content is analyzed more extensively and therefore more accurate and more complete emotion indices could be constructed. Thirdly, while this study does research the difference in the impact of media emotions along the business cycle, an interesting area for future research could be to investigate the possible mechanisms that drive different levels of predictability.

VI. Appendix

Table I
Item Composition of the PANAS-X Scales

The table reports the PANAS-X basic positive, negative and other affective state emotion scales. Each emotion scale comprises a number of terms that together show the highest level of significance, reliability and validity in capturing the emotion (Watson and Clark, 1999).

Basic Positive Emotion Scales	
Self-Assurance	proud, strong, confident, bold, daring, fearless
Attentiveness	alert, attentive, concentrating, determined
Joviality	happy, joyful, delighted, cheerful, excited, enthusiastic, lively, energetic
Basic Negative Emotion Scales	
Fear	afraid, scared, frightened, nervous, jittery, shaky
Hostility	angry, hostile, irritable, scornful, disgusted, loathing
Sadness	sad, blue, downhearted, alone, lonely
Guilt	guilty, ashamed, blameworthy, angry at self, disgusted with self, dissatisfied with self
Other Affective States	
Shyness	shy, bashful, sheepish, timid
Fatigue	sleepy, tired, sluggish, drowsy
Serenity	calm, relaxed, at ease
Surprise	amazed, surprised, astonished



TOPICS IN WALL STREET

Restraint

The more Wall Street discusses the various proposals now before Congress for amendment of the Securities Act of 1933 and the Securities Exchange Act of 1934, the clearer becomes the conclusion that the financial industry actually asked for surprisingly little. The biggest changes in which the Securities and Exchange Commission concurred would provide information for the public on 1,000 to 1,500 unlisted issues, register private placements and permit the commission to exempt from registration a good many issues which are public in name only. Then, the industry suggested abolition of the recapture provision in the subsection dealing with insiders' trading and asked that the commission give up its so-far footless efforts to segregate brokers and dealers. The commission objects to both. Aside from these, the requests of the industry were mostly for changes in smaller technical matters, with many of which the SEC could agree. There seems to have been no disposition to "horse trade," asking for a lot and being willing to accept much less.

Wheat Carryover

With the carryover of wheat from previous crops estimated officially on July 1 at 386,406,000 bushels, the second largest on record, the total domestic supply of that cereal this season will be 1,337,359,000 bushels. Recently the government estimated this year's crop at 950,953,000 bushels. Since the normal domestic consumption of wheat is between 675,000,000 and 700,000,000 bushels annually, there will be available for export and carryover into next season around 650,000,000 bushels of the cereal. Unless there is an improvement in the shipping situation, exports are expected to continue at a low level. However, there is a chance that, under the lend-lease act, exports of the cereal may be larger than they now are expected to be. There is little doubt, however, that the surplus on July 1, 1942, will exceed the record of 393,407,000 bushels carried into the 1933 crop season.

Tax Note Sales

Orders from large corporations and from individuals for the new Treasury tax-anticipation notes are being received at the Federal Reserve Bank in increasing volume. The twelve Federal Reserve central banks, which act for the Treasury in this matter, are not expected to issue figures on their sales of these securities. The daily Treasury statement gives some clue, although there is a normal lag of several days in the reporting. For example, the Treasury statement of Aug. 9 showed sales of tax notes in the amount of $215,722,325, whereas, the actual volume of sales is believed now to be close to $300,000,000. At any rate, sales of the new tax notes this month are more than double the aggregate reported sales of Defense Savings Bonds for the same period. The latter went on sale on May 1, whereas, the tax notes, first offered on Aug. 1, may be purchased at any time this month and still yield interest from Aug. 1.

Rubber Dealings Suspended

At a meeting of the board of governors of the Commodity Exchange, Inc., held yesterday after the close of the market, it was decided to suspend dealings in rubber futures. This action was taken at the request of Leon Henderson, Price Control Administrator, who late on Tuesday had sent a telegram to the Exchange requesting that trading in rubber futures be stopped and all open contracts liquidated at prices prevailing at the close of business on that day. With the cessation of trading in rubber, there are only hides, tin and lead in which the members of the Exchange now may deal. Previously trading in silk and copper futures had been suspended. Since the tin and lead markets are very quiet, the activity of the members of the Commodity Exchange will be restricted severely. So far the price-fixing activities of the government have hit the Commodity Exchange more than any other market.

Sugar Futures

Despite the fact that prices fluctuated widely yesterday on the sugar futures market as a result of the "price ceiling" action taken late Tuesday by Leon Henderson, trading volume was normal and at no time in the session on the New York Coffee and Sugar Exchange did the market show any sign of disorganization. The domestic sugar contract—directly affected by the order—opened 14 to 23 points net lower and then rallied. Closing prices were 12 to 13 points under Tuesday's final prices, with the September option quoted at 2.69 cents a pound. The price ceiling for raw sugar of 3.50 cents a pound—2.60 cents for Cuba sugar before duty—will become effective today. Selling was checked to some extent by reports from Cuba of a varied nature. One said Cuba was considering a minimum price of 2.80 cents a pound, or 20 points above the ceiling; another said that 400,000 tons of "loan" sugar about to be offered to the United States by Cuba would be withdrawn. No deals were reported in the raw spot sugar market.

Investors Return to Tech Stocks As IBM, Compaq, Intel Post Gains

ABREAST OF THE MARKET

By Loren Fox
Dow Jones News Services

NEW YORK – Providing evidence that year-end profit-taking may be winding down, investors returned to technology names Tuesday and boosted stocks in a classic "Santa Claus Rally."

Building on the late-session rebound that blue chips staged Monday, the Dow Jones Industrial Average rose steadily and finished with its sixth-consecutive advance. The Dow industrials rose 33.83, or 0.52%, to close at 6522.85 – the first time it has closed above 6500 in three weeks.

For the first time in several sessions, the market's strength was broad-based and even extended to smaller issues. Standard & Poor's 500-stock index gained 4.11, or 0.55%, to 751.03, and the Russell 2000 index of small-cap stocks rose 0.45, or 0.13%, to 355.87.

Tech issues, which had been depressed by recent profit-taking, recovered. The broader market seemed energized by the revival of computer-related stocks. International Business Machines rose 1½ to 155¾; Compaq Computer rose 2⅜ to 74⅝; and Nasdaq-listed Intel rose 3¼ to 135⅛.

The technology-laden Nasdaq Composite Index gained 8.11, or 0.63%, to finish at 1287.63.

Financial stocks also helped buoy the market, as investors seemed to gain confidence in the steady interest rate environment. Citicorp rose 1⅜ to 106¼, J.P. Morgan rose ⅝ to 99⅝, and Bankers Trust rose ⅝ to 88⅛.

The rise in stocks came despite light pre-holiday volume in a shortened session. With the markets closing at 1 p.m. EST, only 167.2 million shares changed hands on the New York Stock Exchange, fewer than half the nearly 339.5 million shares that were traded in Monday's full session. Advancing issues outnumbered decliners 1,369 to 910.

American Express rose 2⅝, or 4.87%, to 59⅛ amid rumors about an impending announcement. But American Express said it had nothing to add to a statement the company made last week that it isn't engaged in talks with any other firms regarding a sale of all or part of the company. Several analysts speculated that American Express, which earlier this month ended unsuccessful merger talks with Citicorp, might be getting ready to announce a deal over the Christmas holiday. That speculation was fueled after analysts received phone calls from American Express asking for their home telephone numbers. But people familiar with American Express said an employee in the company's investor relations department was simply updating a list of analysts' home phone numbers that the company maintains.

The Dow's Performance
DJIA at 5-minute intervals Tuesday
6530
6520
6510
6500
6490
6480
Market closed at 1 p.m.
Monday's close
9:30 10 11 12 1 2 3 4

AT&T rose 1⅜ to 41⅝. MCI Communications added ⅛ to close at 32⅛ on the Nasdaq Stock Market. The Federal Communications Commission Tuesday unveiled a proposal to overhaul the fees that local phone companies charge to long-distance providers. The plan, in its current form, would ease some costs for long-distance companies.

Global Industries fell ⅛ to 18⅜ on Nasdaq. The company, which provides construction services for the energy industry, bought 49% of a Mexican offshore construction firm from J. Ray McDermott. J. Ray McDermott, an oil-services company, fell ⅛ to 22⅛.

BellSouth rose 1¼ to 39⅝. Smith Barney upgraded its rating on the phone company to buy from outperform, and BellSouth launched a tender offer to buy controlling interest in Tele2000, a Peruvian telecommunications company.

Teva Pharmaceutical rose 1 13/16 to 46⅝ on Nasdaq. Gruntal & Co. upgraded its rating on the pharmaceutical company, following Monday's decision by the Food and Drug Administration to approve Teva's multiple sclerosis drug, Copaxone, for marketing.

Noble Drilling rose ⅞ to 21⅝. The offshore driller said late Monday it contracted a deepwater rig to Shell Oil for four years and it bought a cantilever rig.

Owens-Corning rose ⅛ to 41⅝ after Bear Stearns initiated coverage of the building products company with an attractive rating.

Synetic Inc. fell 1/16 to 52⅛ on Nasdaq. The plastics maker said it will take an undetermined charge in its second quarter in connection with its acquisition of Avicenna Systems, an intranet developer.

Traders and analysts said the market seemed to exhibit the resilience it showed earlier in the year, when investors saw declines in stock prices as buying opportunities. "On balance, the market gave a good account of itself," said Alan Ackerman, senior vice president at Fahnestock & Co. "It was energized somewhat by the fact that tax-selling seems to be out of the way."

Figure 1. Sample columns of "Topics in Wall Street" (left), published in the *New York Times* on August 14, 1941 and "Abreast of the Market" (right), published in the *Wall Street Journal* on December 26, 1996.

Table II

Overview of Columns in Data Sample

The table reports the different columns used in the data sample and the sample periods in which they were published. In total, the complete data sample covers the period between 1890 and 2015, equaling 126 years, and includes 85,570 unique data files. The sample consists of 57,520 columns from the *New York Times* and 28,050 from the *Wall Street Journal*.

Panel A: New York Times	
Sample period	Column name
1894 - 1941	The Financial Markets
1904 - 1951	Topics in Wall Street
1950 - 1966	Sidelights
1966 - 2011	Market Place
2006 - 2012	Stocks and Bonds
2011 - 2014	Economix
2011 - 2015	Dealbook
Panel B: Wall Street Journal	
Sample period	Column name
1890 - 1893	Comment on the Market
1894 - 1898	Early Morning Matter
1901 - 1906	The Monetary Situation
1907 - 1908	Curb Market Notes
1908 - 1926	Broad Street Gossip
1926 - 2015	Abreast of the Market

Table III

Sample Statistics for the Loughran and McDonald Emotion Scales during Recessions and Expansions

The table reports sample statistics for the Loughran and McDonald (2011) emotion scales that are used in this research. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. "Positive" and "Negative" emotion scales are constructed by counting the number of positive and negative words using the Loughran and McDonald (2011) dictionaries, and normalizing these counts by the total number of words in each article. The "Pessimism" variable is constructed by subtracting the "Positive" from the "Negative" emotion scale. All numbers are presented in percentages. Panel A presents the sample statistics for the entire sample period, comprising 34,458 trading days. In Panels B and C, the sample is broken down by business cycle. Panel B contains all trading days during recessions, while Panel C comprises those during expansions. In total, these are 8,995 and 25,463 days, respectively.

Emotion scale	Mean	Median	25%-qnt.	75%-qnt.	Std. dev.
Panel A: All dates					
Positive	0.98	0.99	0.74	1.25	0.45
Negative	1.87	1.84	1.38	2.35	0.86
Pessimism	0.88	0.78	0.25	1.38	0.86
Panel B: Recessions					
Positive	0.96	0.97	0.71	1.25	0.49
Negative	1.77	1.79	1.33	2.30	0.87
Pessimism	0.81	0.72	0.17	1.30	0.82
Panel C: Expansions					
Positive	0.99	0.99	0.75	1.25	0.43
Negative	1.90	1.86	1.40	2.37	0.85
Pessimism	0.91	0.80	0.27	1.40	0.88

Table IV

Sample Statistics for the PANAS-X Positive Emotion Scales during Recessions and Expansions

The table reports sample statistics for the PANAS-X positive emotion scales that are used in this research. These emotion scales are based on Watson et al. (1988) item composition of the PANAS-X scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. Each of the emotion scales is constructed by counting the number of words using a manually constructed emotion index, comprising the terms as constructed by Watson et al. (1988), their synonyms generated through Thesaurus and all their conjugations that represent an emotion. Subsequently, these word counts are normalized by the total number of words in each article. All numbers are presented in percentages. Panel A presents the sample statistics for the entire sample period, comprising 34,458 trading days. In Panels B and C, the sample is broken down by business cycle. Panel B contains all trading days during recessions, while Panel C comprises those during expansions. In total, these are 8,995 and 25,463 days, respectively.

Emotion scale	Mean	Median	25%-qnt.	75%-qnt.	Std. dev.
			Panel A: All dates		
Joviality	0.039	0.026	0.000	0.062	0.052
Self-Assurance	0.090	0.073	0.029	0.131	0.087
Attentiveness	0.009	0.000	0.000	0.000	0.022
			Panel B: Recessions		
Joviality	0.040	0.025	0.000	0.064	0.053
Self-Assurance	0.078	0.063	0.000	0.116	0.082
Attentiveness	0.008	0.000	0.000	0.000	0.021
			Panel C: Expansions		
Joviality	0.039	0.026	0.000	0.061	0.051
Self-Assurance	0.094	0.077	0.032	0.136	0.089
Attentiveness	0.009	0.000	0.000	0.000	0.023

Table V

Sample Statistics for the PANAS-X Negative Emotion Scales during Recessions and Expansions

The table reports sample statistics for the PANAS-X negative emotion scales that are used in this research. These emotion scales are based on Watson et al. (1988) item composition of the PANAS-X scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. Each of the emotion scales is constructed by counting the number of words using a manually constructed emotion index, comprising the terms as constructed by Watson et al. (1988), their synonyms generated through Thesaurus and all their conjugations that represent an emotion. Subsequently, these word counts are normalized by the total number of words in each article. All numbers are presented in percentages. Panel A presents the sample statistics for the entire sample period, comprising 34,458 trading days. In Panels B and C, the sample is broken down by business cycle. Panel B contains all trading days during recessions, while Panel C comprises those during expansions. In total, these are 8,995 and 25,463 days, respectively.

Emotion scale	Mean	Median	25%-qnt.	75%-qnt.	Std. dev.
		Panel A: All dates			
Fear	0.124	0.092	0.034	0.173	0.133
Hostility	0.013	0.000	0.000	0.000	0.030
Guilt	0.010	0.000	0.000	0.000	0.030
Sadness	0.026	0.000	0.000	0.043	0.043
		Panel B: Recessions			
Fear	0.111	0.082	0.024	0.158	0.121
Hostility	0.012	0.000	0.000	0.000	0.030
Guilt	0.009	0.000	0.000	0.000	0.023
Sadness	0.035	0.000	0.000	0.054	0.051
		Panel C: Expansions			
Fear	0.129	0.096	0.037	0.177	0.137
Hostility	0.013	0.000	0.000	0.000	0.030
Guilt	0.010	0.000	0.000	0.000	0.031
Sadness	0.023	0.000	0.000	0.038	0.040

Table VI
Sample Statistics for the PANAS-X Other Affective State Scales during Recessions and Expansions

The table reports sample statistics for the PANAS-X other affective state emotion scales that are used in this research. These emotion scales are based on Watson et al. (1988) item composition of the PANAS-X scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. Each of the emotion scales is constructed by counting the number of words using a manually constructed emotion index, comprising the terms as constructed by Watson et al. (1988), their synonyms generated through Thesaurus and all their conjugations that represent an emotion. Subsequently, these word counts are normalized by the total number of words in each article. All numbers are presented in percentages. Panel A presents the sample statistics for the entire sample period, comprising 34,458 trading days. In Panels B and C, the sample is broken down by business cycle. Panel B contains all trading days during recessions, while Panel C comprises those during expansions. In total, these are 8,995 and 25,463 days, respectively.

Emotion scale	Mean	Median	25%-qnt.	75%-qnt.	Std. dev.
		Panel A: All dates			
Shyness	0.001	0.000	0.000	0.000	0.008
Fatigue	0.006	0.000	0.000	0.000	0.020
Serenity	0.005	0.000	0.000	0.000	0.018
Surprise	0.019	0.000	0.000	0.032	0.034
		Panel B: Recessions			
Shyness	0.006	0.000	0.000	0.000	0.006
Fatigue	0.005	0.000	0.000	0.000	0.018
Serenity	0.006	0.000	0.000	0.000	0.020
Surprise	0.019	0.000	0.000	0.033	0.034
		Panel C: Expansions			
Shyness	0.001	0.000	0.000	0.000	0.009
Fatigue	0.007	0.000	0.000	0.000	0.021
Serenity	0.004	0.000	0.000	0.000	0.018
Surprise	0.019	0.000	0.000	0.032	0.034

Table VII
Sample Statistics for Daily DJIA Returns, 1890 to 2015

The table reports sample statistics for the DJIA returns used in the paper. Panel A gives unconditional sample statistics for the daily log-returns of the DJIA for the period 1890 to 2015. The first row presents the sample statistics; the following two rows break the sample period into NBER recessions and expansions. Panel B reports the estimated coefficients from the model $R_t = (1-D_t)\gamma_1 L_s(R_t) + D_t\gamma_2 L_s(R_t) + \eta X_t + \epsilon_t$, where L_s denotes an s-lag operator, namely, $L_s(R_t) = R_{t-1}, ..., R_{t-s}$, and D_t is a dummy variable that takes on the value one if and only if date t is during a recession. s is set as $s = 5$ throughout the paper. As the set of exogenous variables X_t a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion, D_t, are included. Panel C presents the estimates of a GARCH(1,1) model, where it is assumed that the return equation has a constant mean, $Rt = \mu + \epsilon_t$, but time-varying volatility of the form $\sigma^2_{t+1} = \omega + \alpha_1\epsilon^2_t + \beta_1\sigma^2_t$, where $\sigma^2_t \equiv \text{var}(\epsilon_t)$ is allowed for. The sample period $t+1$ comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Sample Statistics					
	Mean	Median	25%-qnt.	75%-qnt.	Std. dev.
All dates	0.017	0.042	–0.458	0.530	1.078
Expansions	0.040	0.056	–0.413	0.519	0.938
Recessions	–0.046	–0.012	–0.636	0.576	1.399

Panel B: Time-Series Regression					
Expansions	γ_1	t-stat	Recessions	γ_2	t-stat
$(1-D_t)\times R_{t-1}$	0.035	2.42	$D_t \times R_{t-1}$	0.003	0.14
$(1-D_t)\times R_{t-2}$	–0.038	–2.64	$D_t \times R_{t-2}$	–0.035	–1.52
$(1-D_t)\times R_{t-3}$	–0.001	–0.07	$D_t \times R_{t-3}$	0.026	1.33
$(1-D_t)\times R_{t-4}$	0.009	0.88	$D_t \times R_{t-4}$	0.048	2.44
$(1-D_t)\times R_{t-5}$	0.009	0.69	$D_t \times R_{t-5}$	0.017	0.86
	η	t-stat		η	t-stat
I_{Tue}	0.128	6.4	I_{Fri}	0.152	7.6
I_{Wed}	0.132	6.5	I_{Sat}	0.150	6.8
I_{Thu}	0.109	5.4	D_t	–0.079	–5.1

Panel C: GARCH(1,1) Estimates	
	$\omega, \alpha_1, \beta_1$
Constant, ω	0.000
Innovations term, α_1	0.099
Autoregressive term, β_1	0.884

Table VIII

Feedback from the Loughran and McDonald Emotion Scales to the DJIA

The table reports the estimated coefficients β from the model

$$R_t = \beta L_s(M_t) + \gamma L_s(R_t) + \psi L_s(R_t^2) + \eta X_t + \epsilon_t.$$

The dependent variable R_t is the log-return on the DJIA from 1890 to 2015. The variable M_t is one of the emotion scales as constructed by Loughran and McDonald (2011) or the pessimism emotion scale, which is constructed by subtracting the positive from the negative emotion scale. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. The emotion scales are normalized to have unit variance. As the set of exogenous variables X_t, a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion, D_t, are included. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Media Variables

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
M_{t-1}	0.069	4.4	–0.024	–2.6	–0.042	–4.6
M_{t-2}	–0.161	–1.1	–0.027	–2.8	–0.018	–2.0
M_{t-3}	–0.004	–1.6	–0.000	1.3	0.011	1.3
M_{t-4}	–0.023	–1.3	0.035	–0.0	0.006	0.7
M_{t-5}	–0.021	–1.9	0.018	3.9	0.035	4.1

Panel B: Tests

	Positive		Negative		Pessimism	
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_1 = 0$	19.7	0.000	6.6	0.010	21.6	0.000
$\sum_{j=2}^{5} \beta_j = 0$	8.5	0.004	2.7	0.100	8.3	0.004

Table IX
Feedback from the PANAS-X Positive Emotion Scales to the DJIA

The table reports the estimated coefficients β from the model

$$R_t = \beta L_s(M_t) + \gamma L_s(R_t) + \psi L_s(R_t^2) + \eta X_t + \epsilon_t.$$

The dependent variable R_t is the log-return on the DJIA from 1890 to 2015. The variable M_t is one of the PANAS-X positive emotion scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. The emotion scales are normalized to have unit variance. As the set of exogenous variables X_t, a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion, D_t, are included. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Media Variables

	Joviality		Self-Assurance		Attentiveness	
	β	t-stat	β	t-stat	β	t-stat
M_{t-1}	–0.049	–0.4	0.114	1.7	0.032	0.1
M_{t-2}	–0.080	–0.7	–0.043	–0.7	0.003	0.0
M_{t-3}	0.155	1.3	0.057	0.9	0.115	0.5
M_{t-4}	–0.085	–0.7	–0.049	–0.8	0.097	0.4
M_{t-5}	–0.127	–1.0	0.031	0.5	0.306	1.3

Panel B: Tests

	Joviality		Self-Assurance		Attentiveness	
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_1 = 0$	0.2	0.685	3.0	0.084	0.0	0.896
$\sum_{j=2}^{5} \beta_j = 0$	0.4	0.515	0.0	0.972	1.6	0.200

Table X
Feedback from the PANAS-X Negative Emotion Scales to the DJIA

The table reports the estimated coefficients β from the model

$$R_t = \beta L_s(M_t) + \gamma L_s(R_t) + \psi L_s(R_t^2) + \eta X_t + \epsilon_t.$$

The dependent variable R_t is the log-return on the DJIA from 1890 to 2015. The variable M_t is one of the PANAS-X negative emotion scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. The emotion scales are normalized to have unit variance. As the set of exogenous variables X_t, a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion, D_t, are included. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Media Variables

	Fear		Hostility		Guilt		Sadness	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
M_{t-1}	–0.091	–1.7	0.040	0.2	0.173	1.0	–0.312	–1.9
M_{t-2}	–0.076	–1.4	–0.137	–0.8	–0.433	–2.4	0.028	0.2
M_{t-3}	0.052	1.0	0.030	0.2	0.002	0.0	–0.064	–0.4
M_{t-4}	0.093	1.8	–0.255	–1.5	0.271	1.5	0.155	0.9
M_{t-5}	0.033	0.6	0.106	0.6	–0.065	–0.4	0.142	0.8

Panel B: Tests

	Fear		Hostility		Guilt		Sadness	
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_1 = 0$	3.0	0.086	0.1	0.819	1.0	0.318	3.7	0.054
$\sum_{j=2}^{5} \beta_j = 0$	1.6	0.213	0.6	0.429	0.5	0.478	0.7	0.407

Table XI
Feedback from the PANAS-X Other Affective State Scales to the DJIA

The table reports the estimated coefficients β from the model

$$R_t = \beta L_s(M_t) + \gamma L_s(R_t) + \psi L_s(R_t^2) + \eta X_t + \epsilon_t.$$

The dependent variable R_t is the log-return on the DJIA from 1890 to 2015. The variable M_t is one of the PANAS-X other affective state emotion scales. These scales are constructed using a sample period ranging from 1890 to 2015, including the columns that are reported in Table II from the *New York Times* and the *Wall Street Journal*. The emotion scales are normalized to have unit variance. As the set of exogenous variables X_t, a constant term, day-of-the-week dummies, as well as a dummy for whether date t belongs to a recession or an expansion, D_t, are included. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Media Variables

	Shyness		Fatigue		Serenity		Surprise	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
M_{t-1}	0.874	1.5	0.263	1.1	0.977	2.7	0.070	0.4
M_{t-2}	–0.490	–0.6	–0.025	–0.1	0.160	0.5	–0.051	–0.3
M_{t-3}	0.898	1.3	0.284	1.0	0.386	1.2	0.038	0.2
M_{t-4}	–0.234	–0.39	–0.330	–1.2	0.053	0.2	0.175	1.0
M_{t-5}	–0.168	–1.6	–0.487	–1.4	–2.496	–0.8	0.018	0.1

Panel B: Tests

	Shyness		Fatigue		Serenity		Surprise	
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_1 = 0$	2.1	0.147	1.1	0.296	7.4	0.007	0.2	0.693
$\Sigma_{j=2}^{5} \beta_j = 0$	0.6	0.451	1.1	0.299	0.3	0.590	0.3	0.557

Table XII
Feedback from the Loughran and McDonald Emotion Scales to the DJIA along the Business Cycle

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Expansions (β_1)

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	0.054	3.4	–0.015	–1.6	–0.027	–3.1
$(1-D_t)\times M_{t-2}$	–0.019	–1.2	–0.027	–2.8	–0.017	–1.9
$(1-D_t)\times M_{t-3}$	0.012	0.7	0.010	1.1	0.006	0.7
$(1-D_t)\times M_{t-4}$	–0.035	–2.2	0.001	0.1	0.010	1.2
$(1-D_t)\times M_{t-5}$	–0.001	–0.0	0.036	4.0	0.030	3.6

Panel B: Recessions (β_2)

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
$D_t \times M_{t-1}$	0.095	2.5	–0.051	–1.8	–0.085	–3.2
$D_t \times M_{t-2}$	0.037	–0.1	–0.027	–0.9	–0.023	–0.9
$D_t \times M_{t-3}$	–0.033	–1.0	0.017	0.6	0.025	1.0
$D_t \times M_{t-4}$	0.012	0.3	–0.002	0.1	–0.007	–0.3
$D_t \times M_{t-5}$	–0.070	–1.9	0.033	1.3	0.053	2.1

Panel C: Tests

	Positive		Negative		Pessimism	
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	1.0	0.314	1.5	0.217	4.2	0.040
$\Sigma_{j=2}^{5} \beta_{1j} = 0$	3.3	0.068	3.0	0.086	6.7	0.010
$\Sigma_{j=2}^{5} \beta_{2j} = 0$	3.7	0.054	0.6	0.457	1.9	0.172

Table XIII
Feedback from the PANAS-X Positive Emotion Scales to the DJIA along the Business Cycle

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Expansions (β_1)

	Joviality		Self-Assurance		Attentiveness	
	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	–0.011	–0.1	0.110	1.7	0.290	1.2
$(1-D_t)\times M_{t-2}$	–0.092	–0.8	–0.048	–0.8	–0.242	–1.0
$(1-D_t)\times M_{t-3}$	0.245	2.1	0.050	0.8	0.048	0.2
$(1-D_t)\times M_{t-4}$	–0.172	–1.5	–0.085	–1.3	–0.141	–0.6
$(1-D_t)\times M_{t-5}$	0.103	0.8	0.037	0.6	0.159	0.7

Panel B: Recessions (β_2)

	Joviality		Self-Assurance		Attentiveness	
	β	t-stat	β	t-stat	β	t-stat
$D_t\times M_{t-1}$	–0.085	–0.3	0.089	0.5	–0.878	–1.3
$D_t\times M_{t-2}$	–0.037	–0.1	–0.005	–0.0	0.762	1.2
$D_t\times M_{t-3}$	–0.097	–0.3	0.102	0.6	0.405	0.7
$D_t\times M_{t-4}$	0.187	0.6	0.105	0.6	0.898	1.4
$D_t\times M_{t-5}$	–0.709	–2.4	0.031	0.2	0.865	1.3

Panel C: Tests

	Joviality		Self-Assurance		Attentiveness	
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.1	0.824	0.0	0.915	2.7	0.099
$\sum_{j=2}^{5}\beta_{1j}=0$	0.2	0.692	0.2	0.669	0.2	0.662
$\sum_{j=2}^{5}\beta_{2j}=0$	1.7	0.200	0.7	0.412	6.4	0.012

Table XIV
Feedback from the PANAS-X Negative Emotion Scales to the DJIA along the Business Cycle

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Expansions (β_1)								
	Fear		Hostility		Guilt		Sadness	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	–0.093	–1.8	0.163	0.8	0.200	1.2	–0.259	–1.5
$(1-D_t)\times M_{t-2}$	–0.077	–1.4	–0.080	–0.4	–0.347	–1.9	0.190	1.2
$(1-D_t)\times M_{t-3}$	0.083	1.6	0.063	0.3	0.071	0.4	–0.074	–0.5
$(1-D_t)\times M_{t-4}$	0.073	1.4	0.012	0.1	0.258	1.5	0.299	1.9
$(1-D_t)\times M_{t-5}$	0.040	0.8	0.031	0.2	0.004	0.0	0.243	1.5

Panel B: Recessions (β_2)								
	Fear		Hostility		Guilt		Sadness	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$D_t \times M_{t-1}$	–0.051	–0.3	–0.345	–0.9	0.105	0.2	–0.360	–1.1
$D_t \times M_{t-2}$	–0.071	–0.5	–0.394	–0.9	–0.848	–1.5	–0.246	–0.7
$D_t \times M_{t-3}$	–0.122	–0.8	–0.089	–0.2	–0.430	–0.7	0.025	0.1
$D_t \times M_{t-4}$	0.160	1.1	-1.089	–2.6	0.297	0.4	–0.023	–0.1
$D_t \times M_{t-5}$	0.009	0.1	0.321	0.8	–0.393	–0.7	–0.012	–0.0

Panel C: Tests								
	Fear		Hostility		Guilt		Sadness	
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	0.1	0.799	1.3	0.250	0.0	0.885	0.1	0.792
$\Sigma_{j=2}^{5} \beta_{1j} = 0$	2.2	0.138	0.0	0.941	0.0	0.964	5.0	0.026
$\Sigma_{j=2}^{5} \beta_{2j} = 0$	0.1	0.914	2.7	0.100	1.5	0.221	0.1	0.705

Table XV
Feedback from the PANAS-X Other Affective State Scales to the DJIA along the Business Cycle

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t)+\gamma_1 L_s(R_t)+\psi_1 L_s(R_t^2))+D_t(\beta_2 L_s(M_t)+\gamma_2 L_s(R_t)+\psi_2 L_s(R_t^2))+\eta X_t+\epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Expansions (β_1)

	Shyness		Fatigue		Serenity		Surprise	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	0.823	1.3	0.332	1.3	0.841	2.1	0.298	1.6
$(1-D_t)\times M_{t-2}$	–0.205	–0.3	–0.141	–0.5	0.421	1.1	0.020	0.1
$(1-D_t)\times M_{t-3}$	0.226	0.4	0.269	0.9	0.286	0.8	0.163	0.9
$(1-D_t)\times M_{t-4}$	0.031	0.1	–0.399	–1.6	–0.083	–0.2	0.116	0.7
$(1-D_t)\times M_{t-5}$	–1.246	–1.7	–0.423	–1.1	–0.131	–0.4	0.018	0.1

Panel B: Recessions (β_2)

	Shyness		Fatigue		Serenity		Surprise	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$D_t\times M_{t-1}$	1.600	0.7	–0.098	–0.1	1.244	1.7	–0.476	–1.1
$D_t\times M_{t-2}$	–1.491	–0.4	0.483	0.6	–0.686	–0.9	–0.273	–0.6
$D_t\times M_{t-3}$	4.991	1.8	0.405	0.5	0.546	0.8	–0.332	–0.8
$D_t\times M_{t-4}$	–2.397	–1.1	–0.105	–0.1	–0.210	0.3	0.325	0.7
$D_t\times M_{t-5}$	–0.912	–0.4	–0.720	–0.9	–0.470	–.07	0.112	0.3

Panel C: Tests

	Shyness		Fatigue		Serenity		Surprise	
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.1	0.729	0.3	0.578	0.2	0.636	2.6	0.110
$\Sigma_{j=2}^{5}\beta_{1j}=0$	0.9	0.351	1.6	0.210	0.5	0.489	1.0	0.316
$\Sigma_{j=2}^{5}\beta_{2j}=0$	0.0	0.971	0.0	0.967	0.1	0.762	0.1	0.825

Table XVI
Feedback from the Loughran and McDonald Emotion Scales to the DJIA on Mondays and Post-Holiday Days

The table reports the estimated coefficients β from the model

$$R_t = (1-I_t)[(1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1(R_t^2)) + D_t(\beta_3 L_s(M_t) + \gamma_3 L_s(R_t) + \psi_3(R_t^2))] \\ + (1-I_t)[(1-D_t)(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2(R_t^2)) + D_t(\beta_4 L_s(M_t) + \gamma_4 L_s(R_t) + \psi_4(R_t^2))] \\ + \eta X_t + \epsilon_t,$$

where the dummy variable I_t takes on the value one if and only if date $t-1$ was not a trading date, and all other independent variables are defined as in Tables VIII, IX, X and XI. The dependent variable R_t is the log-return on the DJIA index from 1890 to 2015. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
Expansions, Monday/holidays, β_{11}	0.021	0.6	–0.088	–1.7	–0.037	–1.7
Expansions, back-to-back weekdays, β_{21}	0.065	3.2	–0.012	–1.1	–0.027	–2.6
Recessions, Mondays/holidays, β_{31}	0.101	1.8	–0.032	–0.8	–0.104	–2.5
Recessions, back-to-back weekdays, β_{41}	0.091	2.7	–0.059	–2.6	–0.087	–4.2
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	1.2	0.283	1.1	0.306	0.2	0.700
$\beta_{31} = \beta_{41}$	0.0	0.878	0.3	0.566	0.1	0.713
$\beta_{11} = \beta_{31}$	1.5	0.217	0.0	0.906	2.1	0.145
$\beta_{21} = \beta_{41}$	0.5	0.496	3.4	0.065	6.6	0.010

Table XVII
Feedback from the Self-Assurance, Fear, Sadness and Serenity Emotion Scales to the DJIA on Mondays and Post-Holiday Days

The table reports the estimated coefficients β from the model

$$\begin{aligned} R_t =&(1-I_t)[(1-D_t)(\beta_1 L_s(M_t)+\gamma_1 L_s(R_t)+\psi_1(R_t^2))+D_t(\beta_3 L_s(M_t)+\gamma_3 L_s(R_t)+\psi_3(R_t^2))] \\ &+(1-I_t)[(1-D_t)(\beta_2 L_s(M_t)+\gamma_2 L_s(R_t)+\psi_2(R_t^2))+D_t(\beta_4 L_s(M_t)+\gamma_4 L_s(R_t)+\psi_4(R_t^2))] \\ &+\eta X_t+\epsilon_t, \end{aligned}$$

where the dummy variable I_t takes on the value one if and only if date $t-1$ was not a trading date, and all other independent variables are defined as in Tables VIII, IX, X and XI. The dependent variable R_t is the log-return on the DJIA index from 1890 to 2015. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Expansions, Monday/holidays, β_{11}	0.045	0.3	–0.194	–1.9	–0.873	–2.3	0.056	0.1
Expansions, back-to-back weekdays, β_{21}	0.138	1.6	–0.089	–1.4	–0.170	–0.9	1.033	2.4
Recessions, Mondays/holidays, β_{31}	–0.395	–1.3	0.066	0.3	–0.964	–2.1	–0.080	–0.1
Recessions, back-to-back weekdays, β_{41}	0.245	1.6	–0.013	–0.1	–0.037	–0.1	2.030	3.0
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.3	0.606	0.8	0.387	2.9	0.091	1.4	0.240
$\beta_{31}=\beta_{41}$	3.4	0.064	0.1	0.734	3.2	0.075	2.6	0.107
$\beta_{11}=\beta_{31}$	1.6	0.205	1.4	0.240	0.0	0.875	0.0	0.919
$\beta_{21}=\beta_{41}$	0.4	0.550	0.3	0.586	0.2	0.682	1.6	0.212

Table XVIII
Volatility Adjustments, Orthogonal Media Content and Robust Regressions - Loughran and McDonald Emotion Scales

The table reports the estimated coefficients β from the model

$$R_t = (1 - D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All independent variables are as in Tables VIII, IX, X and XI. In Panel A, the dependent variable R_t denotes the normalized log-returns on the DJIA. These are constructed by taking the raw log-returns on the DJIA and dividing them by the estimates σ_t from the GARCH(1,1) model from Panel C of Table VII. In Panels B and C, R_t denotes the log-return on the DJIA average. In Panels A and C, the variable M_t denotes one the emotion scales, as described in Tables VIII, IX, X and XI. In Panel B, the variable M_t is the residual from the model estimated in Tables XXII and XXIII. Estimation in Panels A and B is via OLS. The estimation in Panel C is done using robust linear regression based on the M-estimator of Huber (1981). The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: GARCH-Adjusted Returns						
	Positive		Negative		Pessimism	
	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	3.449	2.1	–1.661	–1.8	–2.329	–2.7
Recessions, $D_t \times M_{t-1}$	4.183	1.5	–2.295	–1.1	–3.798	–2.0
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	0.1	0.824	0.1	0.786	0.5	0.480
$\sum_{j=2}^{5} \beta_{1j} = 0$	1.7	0.189	3.3	0.071	5.6	0.018
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.7	0.390	0.2	0.665	0.5	0.478

Panel B: Orthogonal Media Scales						
	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	0.048	3.0	–0.011	–1.2	–0.023	–2.5
Recessions, $D_t \times M_{t-1}$	0.103	2.7	–0.050	–1.8	–0.088	–3.2
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	1.7	0.188	0.7	0.196	5.1	0.025
$\sum_{j=2}^{5} \beta_{1j} = 0$	0.3	0.600	0.0	0.914	0.3	0.620
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.0	0.900	1.1	0.291	1.4	0.236

Panel C: Robust Regression						
	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	0.036	2.7	–0.130	–1.7	–0.021	–2.9
Recessions, $D_t \times M_{t-1}$	0.039	1.8	–0.029	–1.9	–0.047	–3.3
	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11} = \beta_{21}$	0.0	0.918	0.9	0.357	2.6	0.109
$\sum_{j=2}^{5} \beta_{1j} = 0$	1.8	0.185	1.2	0.268	2.7	0.098
$\sum_{j=2}^{5} \beta_{2j} = 0$	0.0	0.909	0.0	0.762	0.2	0.624

Table XIX
Volatility Adjustments, Orthogonal Media Content and Robust Regressions - Self-Assurance, Fear, Sadness and Serenity

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All independent variables are as in Tables VIII, IX, X and XI. In Panel A, the dependent variable R_t denotes the normalized log-returns on the DJIA. These are constructed by taking the raw log-returns on the DJIA and dividing them by the estimates σ_t from the GARCH(1,1) model from Panel C of Table VII. In Panels B and C, R_t denotes the log-return on the DJIA average. In Panels A and C, the variable M_t denotes one the emotion scales, as described in Tables VIII, IX, X and XI. In Panel B, the variable M_t is the residual from the model estimated in Tables XXII and XXIII. Estimation in Panels A and B is via OLS. The estimation in Panel C is done using robust linear regression based on the M-estimator of Huber (1981). The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: GARCH-Adjusted Returns								
	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	8.712	1.2	–9.754	–1.9	–32.747	–1.8	54.842	1.6
Recessions, $D_t \times M_{t-1}$	8.544	0.7	4.164	0.4	–23.676	–1.1	84.021	1.6
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.0	0.991	1.3	0.256	0.1	0.751	0.0	0.646
$\sum_{j=2}^{5}\beta_{1j}=0$	0.1	0.778	2.7	0.100	2.5	0.115	0.1	0.810
$\sum_{j=2}^{5}\beta_{2j}=0$	0.5	0.462	0.8	0.360	0.4	0.510	0.3	0.619
Panel B: Orthogonal Media Scales								
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	0.105	1.6	–0.094	–1.8	–0.295	–1.7	0.805	2.1
Recessions, $D_t \times M_{t-1}$	0.133	0.7	0.026	0.2	–0.277	–0.8	1.341	1.8
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.0	0.883	0.5	0.471	0.0	0.963	0.4	0.529
$\sum_{j=2}^{5}\beta_{1j}=0$	0.0	0.977	0.9	0.337	2.3	0.131	0.5	0.495
$\sum_{j=2}^{5}\beta_{2j}=0$	1.8	0.184	0.2	0.667	0.3	0.615	0.0	0.903
Panel C: Robust Regression								
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
Expansions, $(1-D_t)\times M_{t-1}$	0.072	1.2	–0.070	–1.7	–0.259	–2.0	0.272	1.0
Recessions, $D_t \times M_{t-1}$	0.178	1.6	0.005	0.1	–0.621	–3.5	0.884	2.0
	F-stat	p-value	F-stat	p-value	F-stat	p-value	F-stat	p-value
$\beta_{11}=\beta_{21}$	0.7	0.396	0.7	0.411	2.7	0.101	1.3	0.249
$\sum_{j=2}^{5}\beta_{1j}=0$	0.7	0.412	4.3	0.038	3.6	0.060	0.0	0.912
$\sum_{j=2}^{5}\beta_{2j}=0$	0.3	0.576	0.3	0.596	1.6	0.206	0.5	0.485

Table XX

Feedback from the Loughran and McDonald Emotion Scales to the DJIA along the Business Cycle - Subsamples

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. From this total amount of trading days, the *New York Times* subsample comprises 27,028 trading days with at least one article. The *Wall Street Journal* subsample comprises 21,632 trading days with at least one article. The t-stats reported are computed using White (1980) standard errors.

	Positive		Negative		Pessimism	
New York Times						
Panel A: Expansions (β_1)	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	–0.011	–0.9	–0.022	–3.5	–0.023	–3.3
$(1-D_t)\times M_{t-2}$	–0.009	–0.8	–0.006	–0.9	–0.003	–0.51
$(1-D_t)\times M_{t-3}$	0.019	1.6	0.010	1.7	0.007	1.0
$(1-D_t)\times M_{t-4}$	0.001	0.1	0.011	1.8	0.012	1.9
$(1-D_t)\times M_{t-5}$	0.015	1.3	0.016	2.8	0.014	2.1
Panel B: Recessions (β_2)	β	t-stat	β	t-stat	β	t-stat
$D_t \times M_{t-1}$	0.062	2.1	–0.019	–1.0	–0.046	–2.1
$D_t \times M_{t-2}$	–0.022	–0.7	–0.042	–2.1	–0.048	–2.3
$D_t \times M_{t-3}$	–0.008	–0.3	–0.001	–0.1	–0.004	–0.2
$D_t \times M_{t-4}$	–0.016	–0.5	–0.011	–0.6	–0.014	–0.7
$D_t \times M_{t-5}$	0.008	0.3	0.045	2.4	0.044	2.1
Wall Street Journal						
Panel C: Expansions (β_1)	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	0.010	0.9	–0.008	–1.2	–0.014	–1.9
$(1-D_t)\times M_{t-2}$	–0.007	–0.7	–0.014	–2.2	–0.013	–1.8
$(1-D_t)\times M_{t-3}$	–0.002	–0.2	–0.000	–0.0	–0.001	–0.1
$(1-D_t)\times M_{t-4}$	–0.012	–1.1	0.002	0.4	0.007	1.0
$(1-D_t)\times M_{t-5}$	0.007	0.7	0.017	3.0	0.019	2.8
Panel D: Recessions (β_2)	β	t-stat	β	t-stat	β	t-stat
$D_t \times M_{t-1}$	0.073	2.9	0.021	1.3	–0.007	–0.4
$D_t \times M_{t-2}$	–0.061	–2.5	–0.040	–2.5	–0.021	–1.1
$D_t \times M_{t-3}$	–0.037	–1.6	0.002	0.1	0.025	1.2
$D_t \times M_{t-4}$	–0.013	–1.6	–0.007	–0.5	–0.008	–0.4
$D_t \times M_{t-5}$	0.006	0.3	0.016	1.0	0.018	0.9

Table XXI
Feedback from the Self-Assurance, Fear, Sadness and Serenity Emotion Scales to the DJIA along the Business Cycle - Subsamples

The table reports the estimated coefficients β from the model

$$R_t = (1-D_t)(\beta_1 L_s(M_t) + \gamma_1 L_s(R_t) + \psi_1 L_s(R_t^2)) + D_t(\beta_2 L_s(M_t) + \gamma_2 L_s(R_t) + \psi_2 L_s(R_t^2)) + \eta X_t + \epsilon_t.$$

All variables are defined as in Tables VIII, IX, X and XI. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. From this total amount of trading days, the *New York Times* subsample comprises 27,028 trading days with at least one article. The *Wall Street Journal* subsample comprises 21,632 trading days with at least one article. The t-stats reported are computed using White (1980) standard errors.

New York Times								
Panel A: Expansions (β_1)	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	–0.055	–1.0	–0.127	–2.8	–0.087	–0.7	0.406	1.4
$(1-D_t)\times M_{t-2}$	–0.055	–1.0	–0.011	–0.2	0.121	1.0	0.169	0.6
$(1-D_t)\times M_{t-3}$	0.053	0.9	0.083	1.9	–0.036	–0.3	0.199	0.7
$(1-D_t)\times M_{t-4}$	0.026	0.5	0.140	3.2	0.259	2.0	0.264	0.9
$(1-D_t)\times M_{t-5}$	0.066	1.1	0.046	1.1	0.166	1.3	0.158	0.5
Panel B: Recessions (β_2)	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$D_t\times M_{t-1}$	0.124	0.8	–0.109	–0.9	–0.234	–0.9	1.201	1.6
$D_t\times M_{t-2}$	–0.173	–1.1	–0.137	–1.1	–0.385	–1.3	–0.606	–0.9
$D_t\times M_{t-3}$	0.234	1.4	–0.174	–1.4	0.138	0.5	0.228	0.4
$D_t\times M_{t-4}$	–0.104	–0.7	0.177	1.4	–0.217	–0.7	0.403	0.7
$D_t\times M_{t-5}$	0.179	1.1	0.095	0.8	0.513	1.7	–0.570	–1.0
Wall Street Journal								
Panel C: Expansions (β_1)	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$(1-D_t)\times M_{t-1}$	0.032	0.7	–0.065	–1.5	–0.288	–1.8	0.557	1.5
$(1-D_t)\times M_{t-2}$	0.065	1.4	–0.088	–1.9	0.081	0.5	0.282	0.7
$(1-D_t)\times M_{t-3}$	0.043	0.9	0.037	0.8	0.109	0.8	0.026	0.1
$(1-D_t)\times M_{t-4}$	–0.125	–2.5	–0.004	–0.1	0.094	0.6	–0.258	–0.7
$(1-D_t)\times M_{t-5}$	0.047	1.0	0.050	1.1	0.263	1.7	–0.163	–0.5
Panel D: Recessions (β_2)	Self-Assurance		Fear		Sadness		Serenity	
	β	t-stat	β	t-stat	β	t-stat	β	t-stat
$D_t\times M_{t-1}$	0.234	1.4	0.086	0.7	0.373	1.2	0.413	0.6
$D_t\times M_{t-2}$	–0.246	–1.5	–0.255	–2.0	–0.386	–1.3	–0.204	–0.3
$D_t\times M_{t-3}$	–0.082	–0.5	–0.002	–0.0	–0.234	–0.8	–0.023	–0.0
$D_t\times M_{t-4}$	0.124	1.4	0.001	0.0	–0.134	–0.4	0.634	0.9
$D_t\times M_{t-5}$	–0.101	–0.7	0.078	0.6	–0.432	–1.3	0.168	0.3

Table XXII
Feedback from Stock Prices to News Content - Loughran and McDonald Emotion Scales

The table reports the estimated coefficients λ and β from the model

$$M_t = (1-D_t)(\lambda_1 R_t + \beta_1 L_s(R_t) + \gamma_1 L_s(M_t)) + D_t(\lambda_2 R_t + \beta_2 L_s(R_t) + \gamma_2 L_s(M_t)) + \eta X_t + v_t.$$

The variable M_t denotes one of the emotion scales, as described in Tables VIII, IX, X and XI. The set of exogenous variables X_t includes those in the specification of the same tables. In Panel A the variable R_t denotes the log-return on the DJIA. In Panel B the variable R_t denotes the normalized log-returns on the DJIA, constructed as in Panel A of Table XVIII. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Using Raw Returns ($\lambda_1, \beta_1, \lambda_2, \beta_2$)						
	Positive		Negative		Pessimism	
	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat
$(1-D_t)\times R_t$	0.094	23.4	–0.143	–25.9	–0.237	–29.4
$(1-D_t)\times R_{t-1}$	0.015	5.4	–0.020	–4.4	–0.034	–6.5
$(1-D_t)\times R_{t-2}$	–0.003	–1.0	0.005	1.1	0.006	1.2
$(1-D_t)\times R_{t-3}$	–0.006	–2.2	0.014	3.1	0.019	3.8
$(1-D_t)\times R_{t-4}$	–0.010	–3.7	0.009	1.9	0.018	3.5
$D_t \times R_t$	0.064	21.9	–0.094	–21.5	–0.158	–29.9
$D_t \times R_{t-1}$	0.011	3.6	–0.014	–3.2	–0.025	–4.5
$D_t \times R_{t-2}$	–0.003	–1.0	0.005	1.2	0.006	1.1
$D_t \times R_{t-3}$	–0.009	–3.0	0.001	0.3	0.008	1.5
$D_t \times R_{t-4}$	–0.009	–2.8	0.020	4.8	0.027	5.3
	F-stat	p-value	F-stat	p-value	F-stat	p-value
Test $\lambda_1 = \lambda_2$	38.4	0.000	48.7	0.000	67.3	0.000
Panel B: Returns Normalized by GARCH(1,1) ($\lambda_1, \beta_1, \lambda_2, \beta_2$)						
	Positive		Negative		Pessimism	
	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat
$(1-D_t)\times R_t$	0.001	35.8	–0.001	–33.8	–0.002	–48.0
$(1-D_t)\times R_{t-1}$	0.000	4.6	–0.000	–3.6	0.000	–5.5
$(1-D_t)\times R_{t-2}$	–0.000	–2.4	0.000	1.5	0.000	2.3
$(1-D_t)\times R_{t-3}$	–0.000	–2.7	0.000	3.7	0.000	4.7
$(1-D_t)\times R_{t-4}$	–0.000	–3.8	0.000	2.3	0.000	3.8
$D_t \times R_t$	0.001	22.4	–0.001	–21.5	–0.002	–32.3
$D_t \times R_{t-1}$	0.000	3.5	–0.000	–2.1	–0.000	–4.0
$D_t \times R_{t-2}$	–0.000	–2.0	0.000	1.5	0.000	2.2
$D_t \times R_{t-3}$	–0.000	–3.6	0.000	0.9	0.000	2.7
$D_t \times R_{t-4}$	–0.000	–2.0	0.000	4.1	0.000	4.5
	F-stat	p-value	F-stat	p-value	F-stat	p-value
Test $\lambda_1 = \lambda_2$	1.6	0.204	4.1	0.440	5.9	0.150

Table XXIII

Feedback from Stock Prices to News Content - Self-Assurance, Fear, Sadness and Serenity Emotion Scales

The table reports the estimated coefficients λ and β from the model

$$M_t = (1-D_t)(\lambda_1 R_t + \beta_1 L_s(R_t) + \gamma_1 L_s(M_t)) + D_t(\lambda_2 R_t + \beta_2 L_s(R_t) + \gamma_2 L_s(M_t)) + \eta X_t + \upsilon_t.$$

The variable M_t denotes one of the emotion scales, as described in Tables VIII, IX, X and XI. The set of exogenous variables X_t includes those in the specification of the same tables. In Panel A the variable R_t denotes the log-return on the DJIA. In Panel B the variable R_t denotes the normalized log-returns on the DJIA, constructed as in Panel A of Table XVIII. The sample period comprises 34,458 trading days, of which 8,995 were during recessions. The t-stats reported are computed using White (1980) standard errors.

Panel A: Using Raw Returns ($\lambda_1, \beta_1, \lambda_2, \beta_2$)

	Self-Assurance		Fear		Sadness		Serenity	
	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat
$(1-D_t) \times R_t$	0.011	16.0	–0.017	–16.6	–0.002	–6.1	–0.000	–1.5
$(1-D_t) \times R_{t-1}$	0.003	6.1	–0.006	–6.0	–0.001	–3.1	–0.000	–1.8
$(1-D_t) \times R_{t-2}$	0.000	0.8	–0.003	–3.3	–0.000	–1.0	–0.000	–1.8
$(1-D_t) \times R_{t-3}$	0.001	2.0	–0.000	–0.5	–0.000	–0.8	–0.000	–2.0
$(1-D_t) \times R_{t-4}$	–0.000	–0.1	–0.001	–0.6	–0.001	–2.3	–0.000	–1.1
$D_t \times R_t$	0.007	11.2	–0.007	–7.3	–0.002	–5.6	–0.000	–0.8
$D_t \times R_{t-1}$	0.003	5.0	–0.004	–4.4	–0.001	–1.7	–0.000	–0.9
$D_t \times R_{t-2}$	0.001	1.3	–0.001	–1.3	–0.001	–2.0	–0.000	–0.8
$D_t \times R_{t-3}$	–0.000	–0.7	–0.001	–1.8	–0.000	–0.8	–0.000	–0.8
$D_t \times R_{t-4}$	0.000	0.5	0.001	1.2	–0.001	–1.7	–0.000	–2.1
	F-stat	p-value	F-stat	p-value	F-stat	p-value		
Test $\lambda_1 = \lambda_2$	14.3	0.000	57.5	0.000	1.4	0.233	0.7	0.408

Panel B: Returns Normalized by GARCH(1,1) ($\lambda_1, \beta_1, \lambda_2, \beta_2$)

	Self-Assurance		Fear		Sadness		Serenity	
	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat	λ, β	t-stat
$(1-D_t) \times R_t$	0.000	19.6	–0.000	–19.1	–0.000	–6.0	–0.000	–1.7
$(1-D_t) \times R_{t-1}$	0.000	5.7	–0.000	–5.9	–0.000	–3.7	–0.000	–2.3
$(1-D_t) \times R_{t-2}$	0.000	0.4	–0.000	–3.0	–0.000	–1.2	–0.000	–2.2
$(1-D_t) \times R_{t-3}$	0.000	1.6	0.000	0.4	–0.000	–0.8	–0.000	–2.1
$(1-D_t) \times R_{t-4}$	–0.000	–0.3	–0.000	–0.6	–0.000	–2.6	–0.000	–1.7
$D_t \times R_t$	0.000	13.1	–0.000	–7.4	–0.000	–5.9	–0.000	–0.6
$D_t \times R_{t-1}$	0.000	4.8	–0.000	–3.1	–0.000	–0.8	–0.000	–1.9
$D_t \times R_{t-2}$	0.000	0.5	–0.000	–0.7	–0.000	–1.4	–0.000	–0.1
$D_t \times R_{t-3}$	–0.000	–0.6	–0.000	–1.6	–0.000	–1.2	–0.000	–1.0
$D_t \times R_{t-4}$	0.000	0.4	0.000	1.8	–0.000	–0.4	–0.000	–2.2
	F-stat	p-value	F-stat	p-value	F-stat	p-value		
Test $\lambda_1 = \lambda_2$	0.0	0.957	34.4	0.000	7.3	0.007	0.5	0.467

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