Anxiety, Excitement, and Asset Prices

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1. Introduction

Stock market participation meets both the emotional and financial needs of investors. Investors are likely to develop emotional connections with stocks, which could alter their perceptions of risk and return associated with their investments. Since market outcomes are difficult to predict, the pleasure of imagined large future gains in the minds of investors can create feelings of excitement. At the same time, they may experience the emotion of anxiety due to the possibility of an extreme loss in the future. A wide range of investor emotions can be mapped into these two broad emotional states of anxiety and excitement, which are likely to alter investors' risk perceptions and/or beliefs (Kuhnen and Knutson, 2011). Even sophisticated investors' decisions may be affected by their emotions (Kuhnen and Knutson, 2011; Tuckett and Taffler, 2012), even if they do not acknowledge this directly (Taffler, Spence, and Eshraghi, 2017).

The role of emotions in decision-making has been a dominant theme in the psychology literature.[2] Financial economists have also recognized the importance of *incidental* emotions such as weather, sentiment, and mood on financial market outcomes (e.g., Hirshleifer and Shumway, 2003; Edmans, Garcia, and Norli, 2007; Antoniou, Doukas, and Subrahmanyam, 2013; Hirshleifer, Jiang, and DiGiovanni, 2020; Obaid and Pukthuanthong, 2021; Edmans et al., 2022). In contrast, the potential impact of *integral* or *fundamental* emotions (e.g., excitement, anxiety, fear, panic, anger, guilt, etc.) on financial decisions and aggregate market outcomes has received less attention in the existing finance literature.[3]

In this paper, we propose a new method for capturing the emotional engagement between investors and firms, and its implications for asset prices. Specifically, we measure the time-varying emotion-induced utility of stocks for investors in terms of the feelings of excitement

[2] Consistent with the psychology literature, we use the terms 'emotion', 'affect', and 'feeling' interchangeably to convey subjective experience (Auchincloss and Samberg, 2012).
[3] *Incidental* emotions are induced by exogenous factors that are unrelated to the current decision (e.g., weather), while *integral* emotions are endogenous as they are generated by considerations of the current decision task itself (e.g., excitement and anxiety). The experience of investing in a firm can generate additional utility beyond the utility from wealth.

and anxiety that they generate. We first construct a market-level, emotion-induced sentiment measure that reflects the aggregate emotional state of the market. Then, we estimate each stock's emotional appeal to investors and examine whether this firm-level measure of sensitivity to shifts in emotion-based market sentiment (i.e., emotion beta) can explain cross-sectional patterns in stock returns.

We conjecture that emotion-induced demand can generate mispricing, particularly in market segments where arbitrage costs are relatively high. Further, the relative extent of investor emotional attachment to particular stocks will determine the duration of this mispricing. When a stock price drops by a large amount, contrarian and value-minded investors may become excited by its recovery prospects.[4] And when the stock price goes up, momentum or trend-chasing investors may perceive such investment opportunities to be very attractive.[5] In both cases, excess buying pressure induced by investor emotions will lead to higher returns in the near future. This idea is echoed and summarized in the June 16, 2023 New York Times article: "Bull or a bear market? It doesn't matter." Different types of investors see buying opportunities in both up and down markets. If the emotion of excitement dominates in both scenarios, we expect upward price pressure in both cases, leading to potential mispricing.

Motivated by these observations, we posit that investor emotions will generate similar price pressure following large increase or decrease in stock prices and the intensity of emotional engagement of investors with the market will dominate the measure of valence (i.e., positivity/negativity), at least in the short-run. For example, when technology stocks underperform market expectations, investors may manifest both excitement and anxiety at the same time. Given its disappointing performance, many investors may be anxious about the

[4] See, for example, "Warren Buffett spends big as stock market sells off; Berkshire Hathaway loads up on energy stocks as inflation soars." (The Wall Street Journal, May 16, 2022).
[5] See, for example, "This bull market is just getting started, traders Bet. Euphoria sweeps the market for stock options." (The Wall Street Journal, June 26, 2023).

sector's future return prospects. However, other investors could view this decline as temporary, and may become excited by the apparent buying opportunities and invest more in such firms. Likewise, when the industry outperforms market expectations, many investors will become more excited about its future prospects, whereas others will be anxious about such stocks being overvalued. In both instances, excitement and anxiety can act together and generate short-term continuations following positive news and short-term reversals following negative news.[6]

To capture the joint influence of anxiety and excitement, which are positively correlated (correlation = 0.30), we add the two measures in constructing our main emotion-based market sentiment index. When considered separately, the anxiety and excitement measures do not have any predictive ability. Specifically, we use the standard bag-of-words technique with keyword dictionaries made up of 134 excitement-related words and 161 anxiety-related words to construct our market-level emotion index (MEI). For each month from January 1990 to September 2022, we measure MEI using the total of excitement and anxiety word counts in newspaper articles to the total number of words in that month.

Our decision to use textual information to capture the emotional state of the market is based on the assumption that news articles are likely to shape the emotional appeal of individual stocks for investors. In particular, media coverage keeps individual stocks and the market alive in investors' minds, and in the spotlight of public discussion (e.g., Engelberg and Parsons, 2011; Engelberg, McLean, and Pontiff, 2018). Recognizing this, and how media reports reflect feelings about the state of the stock market dynamically (see, for example, Tetlock, 2007; Dougal et al., 2012; Shiller, 2019), we use national- and local-level newspaper articles to measure salient contemporaneous investor emotions and use these to construct our aggregate market emotion index. Because the majority of stocks are not actively covered in the media,

[6] This idea is also supported in The New York Times on July 25, 2022: "Why You Should Be Wary of Wall Street's Upbeat Stock Forecasts," which discusses how excitement and anxiety work in tandem.

we consider market-level measure of emotions and then derive individual stock emotion sensitivities to this market-level emotion index.

Conceptually, our approach augments Tetlock (2007) who uses content analysis to measure the degree of "pessimism" in the Wall Street Journal "Abreast of the Market" column to predict market returns. We employ a related 'bag-of-words' approach and wide range of media sources to derive firm-specific emotion sensitivity estimates to capture firm-specific emotional attachment of investors. Our focus is on predictive ability at the individual stock-level compared with Tetlock (2007) and related papers (e.g., Garcia, 2013; Da, Engleberg, and Gao, 2015), which examine predictability at the aggregate market-level.

Similarly, we extend Garcia (2013) who uses Loughran and McDonald (2011)'s dictionary to construct a sentiment measure to predict next day's market return by counting positive and negative words in New York Times articles. In a related way, Da et al. (2015)'s Financial and Economic Attitudes Revealed by Search (FEARS) index uses Internet search volume for economic terms such as 'recession', 'unemployment', and 'bankruptcy' classified as either 'positive' or 'negative' to predict aggregate market returns. In contrast, we consider different newspaper sources and context-specific emotion-reflecting keyword dictionaries to develop our market emotion index. We use this measure to predict firm-level stock returns.

To capture cross-sectional variation in emotional intensity across firms, we estimate individual firm-level stock emotion betas using 60-month rolling regressions of excess stock returns on the market emotion index. The returns of firms with high emotion beta should exhibit greater sensitivity to variation in the overall emotional state of the market. We use the absolute values of emotion beta estimates to quantify the effects of emotion intensity and expect absolute beta to be higher for stocks whose valuations are more subjective and vary to a greater extent with respect to speculative demand, such as those that are small, growth, and costly to arbitrage. Conversely, large value stocks are likely to have lower emotion utility, and less attractive to investors.

We sort stocks into decile portfolios based on emotion beta in the previous month and measure the monthly returns of the resulting portfolios. We find that the high emotion beta portfolio significantly outperforms the low emotion beta portfolio. During the January 1995 to September 2022 period, the high-minus-low portfolio earns value-weighted abnormal returns ranging from 0.53% to 0.75% per month (*t*-statistics = 3.25 to 4.24, respectively) on a risk-adjusted basis. This emotion beta-based trading strategy generates qualitatively similar alphas even when we adjust for risk using factor models with time-varying betas.

We also examine the impact of arbitrage costs using typical limits-to-arbitrage proxies. Our alpha estimates are higher when arbitrage costs are high. In addition, when market-wide mispricing is more pronounced, our emotion beta-based trading strategy generates even higher (lower) alphas. Arbitrageurs do not immediately recognize this emotion beta-driven mispricing and the economic significance of the alpha estimates persists for up to six months. These results indicate that the alpha estimates of emotion beta portfolios capture mispricing of stocks with high emotional sensitivity. As the effect of investor emotions weakens, they pay more attention to fundamentals, arbitrage becomes more effective, and the mispricing is corrected.

In additional tests, we estimate monthly Fama and MacBeth (1973) regressions and find that emotion beta is economically significant. It has a coefficient estimate of 0.23 with *t*-statistic of 3.74. In economic terms, this estimate implies that one standard deviation shift in conditional emotion beta is associated with a $0.23 \times 1.36 = 0.31\%$ shift in the average stock return next month. Further, an inter-decile shift from the lowest to the highest decile in conditional emotion beta is associated with a $0.23 \times 4.04 = 0.93\%$ shift in the average return.

We conduct a range of other tests to reconfirm the robustness of our core findings. In particular, following Baker and Wurgler (2006), we orthogonalize our market emotion index and construct three orthogonalized indices. To orthogonalize our base index, we collect residuals from regressions of MEI on (i) macroeconomy-related indicators (growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions); (ii) macro uncertainty and tone measures, VIX, economic uncertainty index (Jurado, Ludvigson, and, Ng, 2015, UNC), economic policy uncertainty index (Baker, Bloom, and Davis, 2016, EPU), investor sentiment (Baker and Wurgler, 2006, BWSENT), University of Michigan's Consumer Confidence Index, and two positive/negative-based tone measures (Loughran and McDonald, 2011, LN; Henry, 2008, HN); and (iii) including all the measures listed in (i) and (ii). In all cases, we find strong support for our main findings.

In addition tests, we demonstrate that our stock-level emotion beta is distinct and measures a different dimension of investor sentiment. In addition, for robustness, we measure emotion beta using alternative specifications and multiple variation in factor models, and show that emotion-induced beta remains a significant predictor of stock returns. In each case, the high-minus-low trading strategy earns positive and significant abnormal returns.

Next, we investigate whether our emotion beta-based predictability is distinct from the known predictive ability of incidental emotions examined in the extant literature, including seasonal mood (e.g., Hirshleifer et al., 2020), investor sentiment (Baker and Wurgler, 2006), Baker et al.'s (2016) economic policy uncertainty index (EPU), and Bali, Brown, and Tang's (2017) economic uncertainty index (UNC) betas, as well as positivity/negativity-based textual tone (Loughran and MacDonald, 2011; Henry, 2008). Using the Fama-MacBeth estimation framework, we show that emotion beta has a significant coefficient estimate in the presence of these known predictors of returns. This evidence indicates that the impact of emotion-based sentiment is distinct from other known determinants of future stock returns.

In additional robustness tests, we find that our hedge portfolio produces a significant alpha when we consider only the S&P 500 firms, the largest 1000 stocks, or the 1000 most liquid stocks. We also find consistent results and significant alphas during bullish and bearish market states, low and high volatility periods, crisis and non-crisis sub-periods, and sub-periods of high and low investor sentiment. In addition, our results are qualitatively similar across a range of emotion beta-based extreme portfolios. Together, these tests confirm that emotion-induced sentiment has incremental ability to explain cross-sectional patterns in stock returns.

These findings contribute to the growing finance literature that examines the relation between mood, sentiment, weather, and market prices. We focus on the impact of fundamental emotions, such as anxiety and excitement on investor behavior, and demonstrate that these emotions influence asset prices. These findings extend the return predictability literature (e.g., Cohen and Frazzini, 2008; Lou, 2014; Addoum and Kumar, 2016; Lee et al., 2019) and demonstrate that emotion-based sentiment is an important driver of market prices at the individual stock level.[7] In addition, our results add to the news and finance literature by showing that news affects market prices through its impact on investor emotions.

Beyond the empirical asset pricing literature, our findings confirm those of experimental stock markets, which demonstrate that emotions affect investment decisions (e.g., Andrade, Odean, and Lin, 2016; Breaban and Noussair, 2018). More broadly, we contribute to the investment psychology and decision-making literature, showing that fundamental emotions affect investor behavior and stock returns. Specifically, consistent with the affective circumplex model of emotions (e.g., Posner et al., 2005; Posner et al., 2009), we find that emotional intensity of investor engagement with a firm is priced.[8]

[7] In a related study, Kaplanski and Levy (2010) show that media reports capture people's anxiety associated with aviation disasters, which affects asset prices.

[8] The affective circumplex model of neurophysiological processing of emotions focuses on two dimensions: valence (pleasant/unpleasant) and arousal (activation/deactivation). Arousal increases with the intensity of both positive and negative valence. Different emotions of the same valence influence judgments and choices in dissimilar ways (e.g., Lerner and Keltner, 2000; DeSteno et al., 2000). For example, even though fear and anger

One potential caveat with our findings is that the emotional states of investors cannot be directly captured and, as a result, we have used an indirect, text-based approach to capture their emotional states of anxiety and excitement. However, a similar concern applies to other studies that examine the pricing impact of mood and other related measures of sentiment.

2. Data and Measures

2.1 Measuring and quantifying emotions

It is difficult to measure and quantify emotion since it is not directly observed. Our analysis is based on the assumption that newspaper articles would reflect investor feelings about the stock market. The media helps generate and also reflects the emotions of its readers (Shiller, 2017). Unfortunately, newspapers do not regularly cover every firm listed on the three major main stock exchanges (NYSE, AMEX, and Nasdaq). Hillert, Jacobs, and Müller (2014) find the median number of articles published by the national media about a firm in a given year is only three. Most importantly, newspapers cover less than half of the U.S. stock market on the basis of at least one article about a firm per year. Such limited media coverage of many firms poses a barrier to constructing an appropriate dataset at the individual firm level directly.

Our innovation is to collect news articles about the S&P 500 index, which newspapers cover frequently. We use these articles to construct a market-level emotion index. We work with 65,825 articles collected from 21 national and local level newspapers. Appendix Table A1 breaks down the number of articles by newspaper and provides respective period coverage. The four widely-circulated national-level U.S. newspapers - The New York Times, The Washington Post, Wall Street Journal and USA Today - account for about half of our articles.

have the same negative valence, Lerner and Keltner (2001) document that fearful individuals make pessimistic judgements whereas angry individuals make optimistic judgements. In parallel, emotions with opposite valence such as anger and happiness can have a similar influence on judgements. Thus, we work with the intensity of the emotions investors experience rather than just emotional valency.

These news articles are obtained from the Nexis, ProQuest, and Factiva databases using ‘stock index’, ‘S&P 500’, and ‘stock market’ jointly as keywords in the power search functions to identify index-specific news items. In the case of Nexis, we use its “relevance score” measure, and retain all articles with a score of more than 80%. We exclude newswires, non-business news, and websites. ProQuest and Factiva, on the other hand, do not provide any formal relevance score instead ranking articles by keyword relevance. To deal with this issue, we ensure all search keywords are present in the abstract and main text. *Wall Street Journal* articles are downloaded from both ProQuest and Factiva. All databases have good coverage from 1990 onwards, which is why we start the sample period in January 1990.

2.2 Market emotion index

To quantify investor emotions at the firm-level and construct stock emotion betas, we first measure market’s emotional state using news articles about the stock market. To do this, we employ a standard dictionary-based textual analysis approach widely employed in the finance literature (e.g., Liu and McConnell, 2013; Garcia, 2013; Henry and Leone, 2016). Specifically, using the context-specific emotion keyword dictionaries of Taffler, Agarwal, and Obring (2023), we categorize emotional word mentions in news articles in different ways. These lexicons were originally constructed to capture the different market emotions manifest during the highly emotionally-charged dot.com bubble period.

Taffler et al. (2023) also demonstrate empirically a similar range of emotions are salient during the Global Financial Crisis period and Covid-19 pandemic. Their seven-keyword dictionaries measure investor ‘excitement’, ‘anxiety’, ‘mania’, ‘panic’, ‘blame’, ‘denial’, and ‘guilt’, and cover 835 words in total. We perform a principal component analysis (PCA) of word counts of these seven emotion keyword lexicons and find they collapse into two factors. Excitement relates to the first factor, and anxiety explains the second factor. As such, we work only with excitement and anxiety keywords in this paper. Appendix C1 summarizes the lexicon construction method and Appendix C2 lists our excitement and anxiety keywords.[9,10]

We measure the relative strength of different emotions in any month using the frequency of different categories of emotion keywords. Kuhnen and Knutson (2011) draw on neuroscience to investigate investor risk-taking behavior and posit that the two affective states of excitement and anxiety influence risk preferences in the emotional brain. Motivated by their findings, we work with the emotions of excitement and anxiety in our asset pricing tests.

To construct our market emotion index, we start by cleaning the news articles. We convert all words to lower case, and remove numerical values, punctuation, symbols, tables, figures, and standard English stop words (e.g., a, an, and, the, etc.) in line with the natural language processing and the textual analysis literature. We generate emotion word counts using the two keyword lexicons of excitement and anxiety. We generate our market emotion index (MEI) measure as:[11]

$$MEI_t = \frac{Excitement_t + Anxiety_t}{Total\ Words_t}, \tag{1}$$

where $Excitement_t$ and $Anxiety_t$ are the respective excitement and anxiety word counts derived from news articles in month t relative to the total number of words across the articles. Individual words receive equal weights. We standardize our MEI (mean = 0.0 and standard deviation = 1) before using it in our empirical analysis.

[9] To ensure all retained keywords have market relevant meaning when taken in context, Taffler et al. (2023) use five words either side keyword-in-context (KWIC) analysis in developing their lexicons. Thus, although some of the words in the excitement dictionary in Appendix C2 such as 'jump', 'rise', 'run up', and 'winner' etc., and words such as 'caution', 'difficult', 'fall', and 'volatile' etc. in the anxiety dictionary may appear 'neutral' when considered out of context, they convey market relevant meaning in context. For example, "… analysts predict year-over-year S.&P. 500-profit growth to have exceeded 27 percent in the first quarter. That would still be a bigger-than-average jump." (The *New York Times*, April 18, 2010).

[10] Henry and Leone (2016) provide evidence that domain-specific dictionaries, as we use, perform better than general wordlists in the context of financial markets, and also mitigate the problem caused by polysemy, i.e., the capacity of a single word to have multiple meanings.

[11] Traditional tone and sentiment measures use valence. We focus on emotional intensity/arousal (Loewenstein and Lerner, 2003; Posner et al., 2005). In a robustness test, we demonstrate that arousal is more powerful than valence (see Appendix Table A3).

We combine excitement and anxiety word counts to measure market emotions as they jointly capture the overall emotional state of the market. When the market is bullish, excitement is high but at the same time anxiety increases as investors may feel that the market would fall quickly. In contrast, during bearish market conditions, anxiety is greater but investors may also be excited about the opportunities low market prices offer. Thus, excitement and anxiety *jointly* determine the overall emotional state of the market. Figure 1 shows that the total anxiety and excitement emotional word counts over time. Both the Internet bubble and the Global Financial Crisis periods are captured effectively as is Covid-19. We also find expected patterns in anxiety and excitement, for example, following the credit-rating downgrading of the U.S. economy in August 2011, and the collapse in oil prices in early 2016.

We do not use the Loughran and McDonald (2011) (LM) and Henry (2008) (HN) positive/negative (tone) word dictionaries in our main analysis as these dictionaries are not designed to measure investor emotions *per se*, which is the focus of this paper. Further, Loughran and McDonald's lexicons are developed from 10-K reports that contain accounting/financial jargon, which are unlikely to have significant emotional resonance. The Henry (2008) study focuses on two profitable industries and excludes words such as 'adverse', 'loss', 'impairment', and 'missing'. However, when controlling for both Loughran and McDonald (2011) and Henry (2008) narrative tone measures, we find that emotion beta has incremental predictive ability over these valence-based positivity/negativity measures.

2.3. Validation tests

In this section, we examine whether our emotion-based sentiment measure is distinct from traditional sentiment measures.

2.3.1 Correlations with other related measures

Our emotion-based measure differs from other sentiment measures. In fact, our market emotion index has correlations of only 0.02 and 0.04, respectively, with the Baker and Wurgler (2006) investor sentiment index and the University of Michigan's Consumer Confidence Index. Panel A of Table 1 presents the correlations between our market emotion index and other variables. We also observe that our MEI has very low correlation with market-wide volatility measure (VIX), economic and policy uncertainty, and market-wide tone measures.

2.3.2 Orthogonalized market emotion index

The news articles we use to construct the market emotion index may reflect the concurrent state of the economy and macroeconomic uncertainty. We address this potential concern in several ways. We consider search terms are designed specifically to identify news items directly associated with the stock market with a relevance score of 80% or more.[12] Further, we re-estimate our market emotion index after removing words that are potentially related to the macroeconomy from our anxiety and excitement lexicons. Specifically, we drop 'uncertain' and 'uncertainty' from our anxiety keyword dictionary, and exclude 'boost', 'boosts', and 'boosted' from the excitement keyword dictionary.[13,14] In both cases, the resulting market emotion indices have a correlation of more than 0.70 with the main market emotion index.

Next, we orthogonalize our market emotion index in several ways. Following Baker and Wurgler (2006), we regress the base MEI on several macroeconomic indicators and use the residuals as our first orthogonalized index ($MEI^{\perp}$). The set of macro variables includes growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recession periods. Our second MEI residual measure (i.e., $MEI^{\perp\perp}$) is computed by regressing MEI on volatility, macro uncertainty, sentiment, and tone

[12] We examine whether our market emotion index is correlated with the S&P 500 index return and find a contemporaneous correlation of -0.022 between the two. Our one-month lagged MEI has a correlation of 0.145 with the current month's S&P 500 index return. Also, the correlation does not run in reverse as that between one-month lagged S&P 500 index return and current MEI is only -0.046.

[13] Baker et al. (2016) also use the terms 'uncertain' and 'uncertainty' to develop their economic policy uncertainty (EPU) index.

[14] We additionally remove 'shrink', 'shrinks', 'shrinking', 'shrinkage', and 'shrunken' from our anxiety dictionary, and 'booster', 'expand', 'expands', 'expanding', 'expanded', and 'expansion' from our excitement dictionary.

measures. This set of variables includes VIX, the economic uncertainty index of Jurado, et al. (2015, UNC), the economic policy uncertainty index of Baker et al. (2016, EPU), investor sentiment (Baker and Wurgler, 2006, BWSENT), the University of Michigan's Consumer Confidence Index, and the two tone measures of Loughran and McDonald (2011) and Henry (2008). For robustness, we also include all of the indicators together and estimate residuals for our third orthogonalized index ($MEI^{\perp\perp\perp}$). All orthogonalized MEIs are very highly correlated (> 0.95) with our base emotion index (see Panel A of Table 1).

As an alternative to orthogonalization, in our predictive regressions, we control for the Jurado et al. (2015) economic uncertainty and Baker et al. (2016) economic policy uncertainty measures. We also account for time-varying systematic risk exposures associated with business cycles and financial crises in our factor models. Thus, employing different validation methods, we are able to account for both measurement-related concerns and potential economic confounding effects.

2.4. Estimating emotion betas

For each month in our sample period, we estimate a stock's emotion beta using the monthly rolling regressions of excess stock returns on the market emotion index over a sixty-month fixed window while controlling for a variety of asset pricing factors. The first set of emotion betas are generated using data from January 1990 to December 1994. Then, we use these monthly emotion betas to predict the cross-sectional stock returns in the following month. Our rolling window estimation method is similar to that of Bali et al. (2017), and Addoum and Kumar (2016), and uses the following specification:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI*} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t}^{e}$ is the excess return on the stock i in month t. We focus on $\beta_{i,t}^{MEI*}$, stock i's emotion beta. MEI_t is the monthly market emotion index. MKT_t is the monthly excess market return.

X_t includes the following asset pricing factors: size (SMB), book-to-market (HML), profitability (RMW), investment (CMA), liquidity (LIQ), finance (FIN), and post-earnings announcement drift (PEAD) at time t.

In our empirical analysis, we use a conditional measure of β^{MEI*}, defined as $\beta^{MEI} = \left|\beta_{i,t}^{MEI*}\right|$. This choice is based on the idea that stocks with higher emotional utility for investors, irrespective of valence, will have higher β^{MEI}. We focus on the magnitude of the emotion beta for several reasons. First, emotional intensity represents 'arousal' in the circumplex model of affect (Posner et al., 2009) and increases with the absolute value of valence. Arousal represents the power of the emotions individuals experience that we expect to impact investor decisions.

Second, Loewenstein and Lerner (2003) argue that at sufficient levels of intensity, emotion can overwhelm cognitive processing and direct behavior in directions different from those predicted by rational decision-making. In line with this conjecture, we predict that the strength of emotional charge (β^{MEI}) will be more predictive than its valence. Finally, as investors engage emotionally with the stock market, and as they invest in individual stocks, they are likely to experience feelings of excitement and anxiety simultaneously. Consequently, we focus on the overall emotional state of investors. In fact, in untabulated results, we find that neither anxiety nor excitement beta has separate predictive ability.

2.5. Why absolute emotion sensitivities?

We quantify a firm's sensitivity to market emotions. When the stock market is bullish, excited participants will act as trend chasers, and drive prices up further. In parallel, when the market is bearish, with anxiety dominating, contrarian investors are likely to generate price pressure. In both cases, stock prices could go up, generating mispricing, which eventually erodes as investors become more informed. Thus, we expect a *'U-shape'* relation between emotion beta (β^{MEI*}) and stock returns. Figure 2, which reports portfolio returns sorted on unconditional emotion beta, supports this proposition empirically. In both extreme positive and negative cases, returns are positive. This evidence implies that firms with extreme emotion betas have the highest returns, demonstrating the need to work with the absolute beta measure.

This decision is further supported by the evidence in Figure 3, which plots different portfolio characteristics such as size, market beta, annual growth of assets, idiosyncratic volatility etc. across decile portfolios sorted on unconditional emotion beta. In line with our expectation, we find a similar pattern, i.e., both extreme negative (low) and positive (high) emotion beta portfolios have similar firm characteristics, validating the use of a conditional (absolute) measure of emotion beta.

2.6. Emotion betas across industries

We expect certain industries to have higher emotional glitter than others as they are likely to be more in the news because of the nature of their business (Barber and Odean, 2008). To identify whether investors find any particular set of industries more attractive, we examine average emotion sensitivities for each of the Fama-French 48 industries.

We find that emotion beta varies widely across industries. Figure 4 presents industry time-series averages for both our unconditional and conditional emotion beta estimates. In Panel A, we show the average unconditional emotion beta estimates for the top and bottom 5 industries. A large variation is evident in the unconditional emotion beta estimates across the industries. We find that Computers (Comps), Measuring and Control Equipment (LabEq), and Personal Services (PerSv) exhibit the highest positive emotion sensitivities whereas Construction (Cnstr), Textiles (Txtls), and Recreation (Toys) have the most negative emotion betas, indicating that these industries have greater emotional charge for investors.

Similarly, in Panel B, we report the average conditional emotion beta estimates for the top and bottom 5 industries. Emotion beta magnitudes are larger in Panel B than Panel A, as we average absolute values. Here, Pharmaceutical Products (Drugs), Electronic Equipment

(Chips), and Computers (Comps) have the highest conditional emotion betas and Tobacco Products (Smoke), Shipping Containers (Boxes) and Utilities (Util) have the lowest emotional resonance for investors.

2.5 Other return predictors

Monthly stock returns are from the Center for Research in Security Prices (CRSP) database. Market equity and book-to-market data are taken from COMPUSTAT. We work with common stocks with share codes 10 and 11 listed on the NYSE, AMEX, and Nasdaq with share price more than $5 or less than $1,000, and positive book equity. When firms are delisted, we use delisting returns. We require a minimum of 24 monthly observations in any 60-month period, and 15 daily observations in the past one month to be available for our variables.

The Fama-French factors, risk-free rate, and industry classification data are from Kenneth French's data library.[15] The Fama-French factor data includes the excess market return (MKT), small-minus-big (SMB), high-minus-low (HML), winner-minus-loser (UMD), robust-minus-weak (RMW), and conservative-minus-aggressive (CMA) factors. The liquidity factor (LIQ) is from Lubos Pastor's data library.[16] Other monthly factor returns such as profitability (ROE), investment (I/A), finance (FIN), and post-earnings announcement drift (PEAD), are downloaded from the global-*q* data library, Kent Daniel, and AQR websites.

We compute the book-to-market ratio, denoted BM, as book equity scaled by market equity.[17] Following Jegadeesh and Titman (1993), we compute a stock's momentum (MOM) as its cumulative return over a period of 11 months ending one month prior to the estimation month. In line with Jegadeesh (1990) the stock's return over the previous month represents its short-term reversal factor.

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

[16] https://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2018.txt.

[17] Book equity is calculated as book value of stockholders' equity plus deferred taxes and investment tax credit (if available) minus book value of preferred stock (when available).

Following Amihud (2002), we measure the illiquidity (ILLIQ) of stock i in month t as the ratio of daily absolute stock return to daily dollar trading averaged across the month:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{3}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively. A stock is required to have at least 15 daily return observations during any given month. The illiquidity measure is scaled by 10^5.

Consistent with Ang et al. (2006), we compute monthly idiosyncratic volatility of stock i, denoted IVOL, as the standard deviation of the daily residuals in a month from the regression:

$$R_{i,d}^{e} = \alpha_t + \beta_i R_{m,d} + \gamma_i SMB_d + \delta_i HML_d + \varepsilon_{i,d}, \tag{4}$$

where $R_{i,d}^{e}$ and $R_{m,d}$, are excess daily return on stock i and the CRSP value-weighted index respectively. SMB_d and HML_d are the daily size and value factors of Fama and French (1992).

We also use market volatility. Like Ang et al. (2006), we estimate implied market volatility beta using bivariate time-series regressions of excess stock returns on excess market returns, and changes in implied volatility using daily data in a month:

$$R_{i,d}^{e} = \alpha_{i,d} + \beta_{i,d}^{MKT} R_{m,d}^{e} + \beta_{i,d}^{VIX} \Delta VAR_d^{VIX} + \varepsilon_{i,d}, \tag{5}$$

where $R_{i,d}^{e}$ and $R_{m,d}^{e}$, are excess daily return on stock i and the excess market return respectively. ΔVAR_d^{VIX} is the change in the daily Chicago Board of Options Exchange (CBOE) volatility index (VIX) and $\beta_{i,d}^{VIX}$ is the volatility beta of stock i in month t. Daily data for VIX is provided by the CBOE.

Following Bali, Cakici, and Whitelaw (2011), and Bali et al. (2017), demand for lottery-like stocks, denoted MAX, is calculated as the average of the stock's five highest daily returns during month t. A stock is required to have at least 15 daily return observations during any given month to compute MAX. As in Hou, Xue, and Zhang (2015), we compute the annual growth rate of total assets, denoted I/A, as the change in book assets scaled by lagged book assets. We also use annual operating profitability, denoted ROE, measured by income before extraordinary items scaled by one-year-lagged book equity. Finally, we control for the industry effect by assigning each stock to one of the Fama-French ten industry classifications based on Standard Industrial Classification (SIC) codes.

Panel C of Table 1 reports the mean, standard deviation, 25th percentile, median, and 75th percentile of the MEI, emotion beta (β^{MEI}), and characteristics of firms included in our sample. We observe significant cross-sectional variation in firm emotion beta estimates. The variation in firm characteristics such as market capitalization, book-to-market, operating profitability, momentum, and liquidity suggests it is important to control for these variables when examining the cross-sectional return predictability of firm-level emotion beta.

3. Main Empirical Results

3.1 Fama and MacBeth regression estimates

We examine the cross-sectional relation between emotion beta and expected returns using a series of Fama-MacBeth regressions. Table 2 presents the time-series averages of the slope coefficients from the regressions of one-month-ahead stock excess returns on emotion beta (β^{MEI}) after controlling for the known predictors of cross-sectional stock returns. Monthly cross-sectional regressions are estimated using the following specification:

$$R_{i,t+1}^{e} = \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{MEI} + \lambda_{2,t}\beta_{i,t}^{MKT} + \lambda_{3,t}\beta_{i,t}^{VIX} + \lambda_{4,t}X_{i,t} + \varepsilon_{i,t+1}, \quad (6)$$

where $R_{i,t+1}^{e}$ is the realized excess return on stock i in month $t + 1$, $\beta_{i,t}^{MEI}$ is the emotion beta of stock i in month t, $\beta_{i,t}^{MKT}$ is the market beta of stock i in month t, $\beta_{i,t}^{VIX}$ is the volatility beta of stock i in month t, and $X_{i,t}$ is a collection of stock-specific control variables for stock i in month

t (size, book-to-market, momentum, short-term reversal, illiquidity, idiosyncratic volatility, growth in assets, operating profitability, and lottery demand).[18]

Panel A of Table 2 reports Fama-MacBeth time-series averages of the slope coefficients with Newey-West t-statistics in parentheses. We find a positive and statistically significant relation between emotion beta and future stock return, even in the presence of all other control variables, i.e., higher emotion beta firms earn higher returns. For example, the average slope when we control for the market factor (see column 2) is 0.253 with a Newey-West t-statistic of 3.63.[19] To determine the economic significance of this average slope coefficient, we use the average values of the emotion sensitivities in the decile portfolios. Table 3 shows that the difference in emotion beta between high-minus-low decile portfolios is 4.13 - 0.09 = 4.04. If a stock were to move from the lowest to the highest decile of β^{MEI}, the change in the stock's average expected return would increase by 1.02% (= 0.253 × 4.04) per month.

Columns 2 to 6 control for other predictors and the average slope coefficient of β^{MEI} remains positive and significant. In the presence of all control variables, the emotion sensitivity measure β^{MEI} has an estimate of 0.09 with a t-statistic of 2.06 (see column 6). In economic terms, a one-standard-deviation shift in emotion beta is associated with a 0.12% (= 0.09 × 1.35) shift in next month's stock return. These findings are similar when we control for industry returns in columns 7-12. Overall, Fama-MacBeth regression estimates are consistent with our

[18] We report the correlation between emotion beta and firm characteristics in Table 1, Panel B. The stock-specific emotion beta has low but negative correlations with size, book-to-market, and operating profitability (ρ = -0.08, -0.02, and -0.02). Emotion beta also has low positive correlations with momentum, reversal, idiosyncratic volatility, growth in assets, and lottery demand (ρ = 0.09, 0.02, 0.20, 0.05, and 0.19). These low correlations with the firm specific risk factors provide initial evidence that our emotion-based measure captures incremental information not contained in other known determinants of average returns.

[19] It is possible that the asset pricing effect we document is capturing some nonlinear market beta or volatility effect. To rule out this possibility, we perform a placebo test as follows: we run a Fama-MacBeth regression with the market and volatility betas, but instead of our emotion beta, we include the absolute value of the market beta. We find the coefficient for the absolute value of the market beta is small and insignificant. This test provides evidence that our results are unlikely to reflect nonlinear market beta or volatility effect.

conjecture that emotion beta is positively related with future stock returns. This effect of investor emotions is distinct from the effects of other known return predictors.

3.2 Univariate sorts

To provide further evidence of emotion-driven return predictability and account for differences in emotion beta portfolios, we examine the predictability and risk-adjusted performance of emotion-based trading strategies using various factor models. In particular, we create decile portfolios and compute value-weighted portfolio returns. Portfolios are rebalanced each month.

Table 3 reports emotion beta portfolio characteristics. Average firm size monotonically decreases from low to high emotion beta decile portfolios. Further, high emotion beta stocks have lower book-to-market (B/M) than low emotion beta stocks, which is consistent with the expectation that small, growth stocks would be more emotion sensitive than large, value stocks. High emotion beta firms also have lower operating profitability (ROE), and higher market beta (β^{MKT}), growth in assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and lottery-like features (MAX). Across all these characteristics. the high emotion beta stock portfolio differs significantly from the low emotion beta portfolio.

Table 4 reports portfolio average excess returns across emotion beta decile portfolios. Specifically, we examine whether high-minus-low emotion beta portfolios generate average excess returns across two different return adjustment models. For each month, we form decile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}) using different return adjustment models, where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the past month.

We present both raw and adjusted stock returns. We use Fama-French 48-industry returns to obtain industry-adjusted returns. Average excess returns on the value-weighted portfolios are presented in columns 1-2, and the last row reports high-minus-low portfolio average excess returns. In line with our main conjecture, we find that investors earn economically significant average excess returns of 0.58-0.65% per month (t-statistics ranges from 2.04 to 2.68) by going Long (Short) in the undervalued (overvalued) high (low) emotion beta portfolios. The evidence is again consistent with investors deriving emotional utility from high emotion beta stocks, and that this influences their investment decisions accordingly.

Next, we examine the ability of emotion-based trading strategies to generate economically significant alphas. Columns 3-6 of Table 4 reports univariate portfolio results. For each month, we again form decile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}) for the previous month. The columns of Panel B of Table 4 present risk-adjusted abnormal returns (alphas) relative to different factor models: (i) α_{FF5} is the intercept from the regression of the excess portfolio returns on a constant, and the market (MKT), size (SMB), value (HML), operating profitability (RMA), and investment (CMA) factors of Fama and French (2015); (ii) α_q is the alpha relative to the market (MKT), size (SMB), investment (IVA), and operating profitability (ROE) factors of Hou et al. (2015); (iii) α_{BS6} is the alpha generated from the regression of the excess portfolio returns on a constant and the Barillas and Shanken (2018) factor model - market (MKT), size (SMB), momentum (MOM), value factor of Asness and Frazzini (2013, HML), operating profitability (ROE), and investment (IVA) factors of Hou et al. (2015); and (iv) α_{DHS3} is the alpha relative to the market (MKT), finance (FIN), and post-earnings announcement drift (PEAD) factors of Daniel et al. (2020).

The third column of Table 4 shows that α_{FF5} increases from -0.17% to 0.37% per month. The difference in value-weighted alpha between the high-β^{MEI} and low-β^{MEI} decile portfolios is 0.53% per month, with a Newey-West t-statistic of 3.25. The other columns with different models show similar results. These alpha estimates indicate that even after accounting for known risk factors, the average return difference between high-β^{MEI} and low-β^{MEI} stocks remains positive and highly significant.

The last three columns of Table 4 present parallel evidence for β^{MEI} value-weighted portfolios. Consistent with the results for α_{FF5}, value-weighted α_q, α_{BS6}, and α_{DHS3} alpha differences between high-β^{MEI} and low-β^{MEI} portfolios are also positive and significant: α_q= 0.75% per month (t-statistic = 4.24), α_{BS6} = 0.72% per month (t-statistic = 4.32); and α_{DHS3} = 0.71% per month (t- statistic = 3.37). Overall, these univariate sorting results support our key conjecture that high emotion beta stocks earn higher returns than low emotion beta stocks.

3.3 Alpha estimates for limits-to-arbitrage and mispricing subsamples

Portfolio characteristics reported in Table 3 indicate that high emotion beta stocks are small, growth, less profitable, more volatile, illiquid, and lottery-like. These stocks are likely to be of a speculative nature, and thus emotionally charged and more attractive to investors, and hence more difficult to value and arbitrage, making them prone to mispricing (Baker and Wurgler, 2006). We conjecture firm-specific emotion beta alphas will be more prominent when arbitrage is costly, and mispricing is more prevalent. To test this idea, we examine whether emotion beta-based alpha is more pronounced for high limits-to-arbitrage and mispricing subsamples.

First, we examine limits to arbitrage employing several proxies. We estimate idiosyncratic volatility as described in sub-section 2.5 above. Following Wang and Yu (2013), we measure dollar trading volume (DOLLTV) as the average of stock trading volume multiplied by price over the previous 12-months. Lower dollar volume implies higher price pressure and hence higher arbitrage costs. We compute bid-ask (B/A) spread as $2 \times |(Price - (Ask + Bid)/2|/Price$ then take the average of over the previous 12-months. For trading costs, the higher the bid-ask spreads the higher the arbitrage costs. We estimate cash flow volatility (CFVOL) as the standard deviation of cash flow from operations over the previous 5 years. Cash flow volatility increases uncertainty, and the greater the uncertainty the more difficult it is to arbitrage. Finally, we calculate turnover (TURN) as the average of trading volume multiplied by price over the previous 12-months. Turnover is related to liquidity, and thus the lower the turnover higher the arbitrage costs. For each arbitrage proxy measure in each month, we divide our full sample in to high and low subsamples based on median values.

Panel A of Table 5 reports the high-minus-low decile portfolio alphas, across the two subsamples for different limits-to-arbitrage proxies. In all cases, we find that our emotion beta-based strategy generates positive and significant alphas when it is costly to arbitrage. For example, for the high bid-ask spread (i.e., high trading costs) subsample (column 3) the emotion beta sorted high-minus-low portfolio generates significantly higher alphas (about 1.20% per month) compared to the subsample when bid-ask spread is low (about 0.45% per month). We find qualitatively similar results with the other proxies. These results demonstrate how high emotion beta stocks are more difficult to arbitrage.

Next, we investigate whether emotion beta-based alphas are associated with mispricing. If emotion beta premium captures mispricing, then it should be more pronounced when mispricing is more common. In line with prior literature, we employ several mispricing proxies to identify mispricing. Following Stambaugh and Yuan (2017), we measure net stock issuance as the annual log change in split-adjusted shares outstanding where split-adjusted shares equals shares outstanding (CSHO) times the adjustment factor (ADJEX_C). We compute composite equity issuance as the growth in the firm's total market value of equity minus the stock's rate of return. We then subtract the 12-month cumulative return from the 12-month growth in equity market capitalization. We estimate asset growth as the annual growth rate of total assets. We calculate momentum as the cumulative returns from month $t-12$ to month $t-2$. Finally, return on assets is the ratio of earnings to lagged assets. For each of these proxies in each month, we divide our sample in high and low subsamples based on the median values.

Panel B of Table 5 presents the high-minus-low decile portfolio alphas across our two subsamples. For all mispricing proxies, we find our emotion beta-based strategy produces positive and significant alphas when mispricing is more prevalent. For example, for the high composite equity issuance subsample (column 2) emotion beta sorted high-minus-low portfolio generates significantly higher alphas (about 1.10% per month) compared to the subsample when composite equity issuance is low (about 0.20% per month). We find qualitatively similar results with the other proxies which indicates that emotion beta leads to mispricing. Taken together, our limits to arbitrage and mispricing analyses provides support for our conjecture that investors become emotionally engaged with stocks and this is stronger when it is costly to arbitrage, and mispricing is more pronounced.

3.4 Alpha estimates using conditional factor models

To further investigate whether time-varying exposures to systematic risk and business cycles drive the abnormal performance of emotion beta-based trading strategies, we account for these using conditional factor models. We consider a range of conditional macroeconomic factors, which vary with the U.S. business cycle and estimate portfolio alpha. Specifically, we interact each return factor with the following variables: (i) an NBER Recession indicator (REC) which takes the value of one during recession periods and zero otherwise. Alternatively, we use the indicator EXTMKT for the dot.com bubble and the Global Financial Crisis periods; (ii) the *cay* residual of Lettau and Ludvigson (2001); (iii) the paper bill spread, the difference between commercial paper yield and 30-day Treasury bill rate; (iv) the term spread, the difference between 10-year and 1-year government bond yield; and (v) the default spread, the difference between BBB and 1-year government bond yield.

We report conditional alpha estimates and factor exposures in Table 6. Columns 1 to 6 control for five Fama-French factors, momentum, and LIQ factors, and their interaction with each systematic risk factor respectively. The last two columns include the interaction of five Fama-French factors, momentum, and LIQ factors with all time-varying systematic risk factors at the same time. The last row presents the differences between high and low deciles.

We find that even after controlling for other conditional factors, the high-minus-low portfolio alpha is economically significant across all models. For example, when we interact the Fama-French factors with NBER Recession, or with the *cay* residual, high-minus-low emotion beta portfolio alphas are 0.48% and 0.53%, respectively, with *t*-statistics of 2.72, and 2.98 (columns 1 and 3). Alpha remains significant when we take into account all the time-varying systematic risks simultaneously (columns 7 and 8). These estimates are very similar to the unconditional factor model alpha estimates of 0.43% and 0.44% in Table 4 (column 1).

Overall, these conditional factor model estimates are similar to the results from the unconditional models. These findings again provide evidence in favor of our key conjecture that higher emotion beta would be associated with higher stock returns.

3.5 Emotion beta persistence and alpha longevity

The emotion sensitivities we document in Table 4 are for the portfolio formation month, not for the following month over which we measure average return. We demonstrate that investors earn a higher abnormal return from high emotion beta stocks in the next month, but does this pattern persist in the future, and for how long?

We begin by estimating cross-sectional regressions of β^{MEI} on the previous 12 months' β^{MEI}s and lagged cross-sectional predictors. Specifically, each month, we run a regression across firms of 1-year ahead β^{MEI} on lagged β^{MEI} and the following lagged cross-sectional return predictors: market beta (β^{MKT}), market capitalization (Size), volatility beta (β^{VIX}), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth in book assets (I/A), operating profitability (ROE), and lottery demand (MAX).

Column 1 of the first row of Table 7 presents the univariate regressions of β^{MEI} on previous 12 months' β^{MEI}. The coefficient is large and statistically significant, which implies that stocks with high β^{MEI} exhibit a similar pattern in the following 12 months. We repeat the same process for up to 5 years ahead, and continue to find statistically significant results. The second row of Table 7 shows that after adding cross-sectional return predictors, coefficients remain large and significant. β^{MEI} persists up to 60 months into the future, indicating that past emotion betas predict future emotion betas.[20] These results also demonstrate that emotion betas differ from other firm characteristics.

Next, we examine the performance of the high-minus-low emotion beta portfolio as the gap between portfolio formation month and emotion beta-based portfolio return estimation month increases. If the abnormal performance of the high-minus-low portfolio reflects emotional charge-induced mispricing that is eventually corrected, performance estimates should weaken as the lag increases.

Figure 5 shows the effect of varying the portfolio formation lag from 1 to 18 months on monthly Fama-French 5-factor abnormal returns. As the gap between portfolio formation period and portfolio return measurement period increases, the abnormal return becomes weaker, both in economic terms, and statistical significance. The abnormal return of high emotion beta stocks is corrected by the market in about 6 months. This evidence suggests that the impact of emotion-based sentiment decays over time.

3.6 Is emotion beta capturing another known pricing effect?

In this section, we examine the extent to which emotion beta has incremental predictive ability over incidental emotions such as mood, investor sentiment, uncertainty, and narrative tone. To test the distinctiveness of our emotion beta (β^{MEI}), we estimate mood (β^{Mood}), sentiment (β^{SENT}), uncertainty (β^{UNC}), and tone (β^{LM}, and β^{HN}) betas by running rolling regressions similar to equation (2). We first examine their correlations, and then include them in Fama-MacBeth regressions.

[20] Our analysis follows Bali, Brown, and Tang (2017) who report similar results for their uncertainty beta in the context of the ICAPM.

The correlation matrix in Appendix Table A2, shows that emotion beta is not strongly correlated with mood, investor sentiment, uncertainty, or tone betas. In fact, the highest correlation is only 0.25 with mood beta. All other correlation coefficients are below 0.1. Thus, we have preliminary evidence that our emotion-based sentiment measure is capturing something distinct from mood, investor sentiment, uncertainty, and tone. To better understand how our integral emotion beta differs from such incidental emotion betas, we examine their individual relations in more detail.

3.6.1 Is emotion beta capturing mood?

To provide evidence that our emotion beta does not capture the effects of mood, we estimate mood beta following Hirshleifer et al. (2020). For each stock, we run a 5-year rolling window regression of the stock's excess returns during high and low mood months ($R_{i,MoodMonth}$) on contemporaneous equal-weighted CRSP excess returns ($XRET_{A,MoodMonth}$):

$$R_{i,MoodMonth} = \alpha_i + \beta_{i,month}^{Mood} XRET_{A,MoodMonth} + \varepsilon_i, \quad (7)$$

where $\beta_{i,month}^{Mood}$ is the mood beta. The regression includes 8 months each year: four pre-specified (January, March, September, and October), and four realized high and low mood months (the top two and bottom two months with the highest and lowest realized equal-weighted CRSP market returns). Hirshleifer et al. (2020) specify January and March as their high mood period, and September and October as their low mood period based on the SAD effect identified in Kamstra et al. (2003).

Table 8, column 1 reports the results of the cross-sectional Fama-MacBeth regressions, controlling for mood beta, firm characteristics, and other risk-factors. Even after accounting for mood beta, β^{MEI} has a significant coefficient with a *t*-statistic of 2.41. This result is not surprising as investors' emotions and their mood drive investment decisions in different ways. Mood is by definition unrelated to the decision at hand, whereas the emotions are integral to the actual judgement (Lerner et al. 2015).

3.6.2 Is emotion beta capturing sentiment?

Next, we demonstrate that our emotion beta is distinct from measures of investor sentiment. We estimate two separate sentiment betas by running the following 60-month rolling window regressions for each stock's excess returns on the Baker and Wurgler (2006)[21] sentiment index orthogonalized for macro-variables, and the University of Michigan's consumer confidence index (UMCCI)[22], while controlling for factors included in equation (2):[23]

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{SENT} SENT_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t,} \tag{8}$$

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{UMCCI} UMCCI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t,} \tag{9}$$

where $\beta_{i,t}^{SENT}$ is the sentiment beta, and $\beta_{i,t}^{UMCCI}$ is the consumer confidence beta.

Table 8 columns 2 and 3 presents Fama-MacBeth regression estimates, where we control for Baker and Wurgler and UMCCI sentiment betas. We find that emotion beta shows incremental economically significant predictive ability with coefficients of 0.12, and 0.09 and *t*-statistics of 2.50, and 2.42, respectively. Thus, emotion beta is different from sentiment betas and has incremental ability to explain the cross-sectional variation in returns.

3.6.3 Is emotion beta capturing policy uncertainty?

It is possible that economic and policy uncertainties are driving our results as high-(low-)levels of uncertainty may arouse feelings of anxiety (excitement) and/or negative (positive) sentiment. Further, the news articles may include economy-wide news related to the stock market. To examine this possibility, we control for the uncertainty beta of Bali et al. (2017), which is derived from the one-month ahead economic uncertainty index of Jurado et al. (2015).

[21] Baker and Wurgler (2006) investor sentiment index is available at http://people.stern.nyu.edu/jwurgler/.

[22] University of Michigan's consumer confidence index is from the Federal Reserve Bank of St. Louis.

[23] We also estimate manager sentiment beta using the manager sentiment index of Jiang et al. (2019). This index is based on the positive and negative tones of conference calls and financial statements. The index is available for a period of 12 years (2003-2014) but as we estimate rolling regressions of 60-months to measure beta, we are left with only 7 years of data. We find that our results remain unchanged when we control for manager sentiment beta.

We estimate uncertainty beta by estimating a 60-month rolling window regression of each stock's excess returns on the uncertainty index and all other factors included in equation (2):

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{UNC} UNC_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t}, \tag{10}$$

Here, $\beta_{i,t}^{UNC}$ is the uncertainty beta. We estimate the Fama-MacBeth regression of a stock's excess return on previous month emotion beta, controlling for the uncertainty beta (β^{UNC}). We also obtain the policy uncertainty beta using Baker et al.'s (2016) economic policy uncertainty index (EPU). Policy uncertainty beta is estimated using a 60-month rolling window regression of each stock's returns on the economic uncertainty index, and the factors in equation (2):

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{EPU} EPU_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t}, \tag{11}$$

where $\beta_{i,t}^{EPU}$ is the policy uncertainty beta. We then estimate the Fama-MacBeth regression of excess return on previous month emotion beta and lagged control variables.

Table 8 columns 4 and 5 report the Fama-MacBeth regressions controlling for the two uncertainty betas. Emotion beta has incremental predictive ability in both cases with coefficients of 0.09 and 0.09 and *t*-statistics of 2.31 and 2.26 respectively. Thus, we conclude that emotion betas do not capture the effects of economic uncertainty.

3.6.4 Is emotion beta capturing tone?

We further show that our market emotion index is distinct from popular text-driven tone measures based on the positive/negative word dictionaries of Loughran and McDonald (2011) and Henry (2008) applied to the same news articles we use to derive MEI.[24]

First, we look for potential commonality across LM's positive/negative and our emotion-based word lists. Table A4 presents the 10 most frequently used emotional and tonal words in our corpus. In the case of 'excitement' and 'positive' words, only "boost" and "confident" are

[24] The LM tone measure is defined as $LM_t = \frac{Positive_t - Negative_t}{Positive_t + Negative_t}$ and HN tone is $HN_t = \frac{Positive_t - Negative_t}{Positive_t + Negative_t}$,where $Positive_t$, $Negative_t$ are the number of positive and negative word counts during month *t*, respectively.

common, while only “fear” and “volatile” are common in the ‘anxiety’ and ‘negative’ word lists. These top 10 word counts suggest there is little similarity between the two sets of lexicons, and that emotion and tone measure different aspects of market behavior.

Next, we assign our news articles across MEI and tone score quintiles in Table A5. If both MEI and tone are measuring the same thing, then the diagonal elements should account for most of the news articles. However, the diagonal elements only account for about 23% of the articles in total, demonstrating that the market emotion index and tone are measuring different dimensions of information.

Third, to reinforce further this point, we present two sample news articles that have very different emotional and tonal scores (see Appendix B). The first article (*The New York Times*, November 29, 2009) elicits emotions of excitement and anxiety and with the market emotion index score = 0.04, which is in the top quartile of all MEIs (Table 1, Panel A). However, the LM tone is neutral with a score of 0.0. Careful reading of the articles shows that the stock market is doing well, which investors find exciting but, they may also exhibit some anxiety that the market may fall quickly.

The second article (*The Wall Street Journal*, January 13, 2004) has a market emotion index = 0.02, again well within the top quartile, reflecting the emotional message conveyed by the news. Again, the main reason for the high MEI is clear in the first sentence of the article: “After seven weeks of market gains, stocks began the new week with yet another advance amid optimism about coming fourth-quarter earnings reports”. Nonetheless, LM tone remains neutral (= 0.00). These two news articles illustrate how the market emotion index and tone are measuring quite different things.

Finally, we estimate tone beta using the following specifications, and examine whether emotion beta still has any incremental predictive ability in the presence of tone betas.

Specifically, we estimate a 60-month rolling window regression for each stock's excess returns on LM and HN tone respectively, after controlling for factors listed in equation (2):

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{LM} LM_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t,} \tag{12}$$

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{HN} HN_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t} X_t + \varepsilon_{i,t,} \tag{13}$$

where $\beta_{i,t}^{LM}$ and $\beta_{i,t}^{HN}$ are the two tone betas. We then run the respective Fama-MacBeth regressions of stock excess return on the previous month's conditional emotion beta, tone sensitivity, and lagged control variables.

Table 8, columns 6 and 7 report the results of the two cross-sectional regressions. Again, even after accounting for the LM and HN tone measures, β^{MEI} has significant coefficients (*t*-statistics = 2.34 and 2.49, respectively). We confirm the stock's emotional charge is capturing something quite different from positive/negative tone measures.

Finally, when we include all mood, sentiment, uncertainty, and tone betas together in a multivariate Fama-MacBeth regression, we find that emotion beta has economically significant predictive ability (see columns 8 and 9). Based on the results in Table 8, we conclude that emotion beta's ability to explain the cross-section of future stock returns is distinct from the known effects of mood, sentiment, uncertainty, and narrative tone.

3.7 Bivariate sorts

In previous tests, we do not control for various firm characteristics when constructing portfolios and estimating alphas. This subsection examines the relation between emotion beta and future stock returns in more detail by performing bivariate portfolio sorts.

Specifically, we perform bivariate portfolio-level analysis of emotion beta stocks using the following four firm characteristics and market beta (β^{MKT}): market capitalization (SIZE), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), and cash flow volatility (CFVOL). Table 8 reports the results of the conditional bivariate sorts between individual firm characteristics and emotion beta. We report value-weighted seven-factor alphas relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors.

First, we condition on market capitalization (SIZE) by forming decile portfolios based on SIZE. Then, within each SIZE decile, we further sort stocks based on emotion beta (β^{MEI}) into decile portfolios. We average portfolio returns across the 10 SIZE deciles to produce decile portfolios with dispersion in β^{MEI}, but that contain stocks across all market capitalizations (see Bali et al., 2017). This process creates a set of β^{MEI} portfolios with very similar levels of market capitalization, and hence controls for differences in SIZE.

The first column of Table 9 shows that after controlling for SIZE, the difference in the abnormal return spread between high and low emotion beta small stocks is 0.44% per month with a *t*-statistic of 2.48. Thus, firm size cannot explain the high (low) returns earned by high (low) emotion-sensitive stocks.

We repeat the same procedure with market beta, illiquidity, idiosyncratic volatility and cash flow volatility separately. After controlling for each of these firm characteristics, we find that high-minus-low emotion beta trading strategy still produces positive and significant alphas. Our results indicate that well-known cross-sectional return predictors cannot explain the emotion beta premium.

Harvey, Liu, and Zhu (2016) suggest that a five percent level of significance for a new factor is too low a threshold, and recommends stricter requirement of a *t*-statistic above 3.0. Table 2 shows that our emotion beta in Fama-MacBeth cross-sectional regressions meets this hurdle in most cases, with *t*-statistics ranging between 3.40 and 4.01, and only drops below this level (*t*-statistic = 2.06 and 2.30) when we control for all risk factors along with industry controls. In parallel, we find in Table 4 that the value-weighted emotion beta alphas pass this test with *t*-statistics ranging from 3.25 to 4.24. With virtually all *t*-statistics very close to or greater than 3.00, we ensure that emotion beta-based alpha reflects the incremental pricing effects of emotions.

4. Additional Results

We perform several additional tests to ensure the robustness of our findings.

4.1 Alternative measures of emotion beta

In the first test, we examine whether alternative measures of emotion sensitivity (β^{MEI}) predict future stock returns. In our baseline analysis, we control for 11 factors in generating emotion beta using equation (2). It is possible that with additional control variables, our evidence of mispricing and predictability weakens.

To test this possibility, we use three alternative measures of β^{MEI}. First, we control for the market (MKT), then second, the market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA) factors, and finally, the market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA), and momentum (MOM) factors:

Model 1:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{a}} + \beta_{i,d}^{MKT} MKT_t + \varepsilon_{i,t}, \tag{14}$$

Model 2:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{b}} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + +\beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \varepsilon_{i,t}, \tag{15}$$

Model 3:

$$R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{c}} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{MOM} MOM_t + \varepsilon_{i,t}, \tag{16}$$

After computing $\beta^{MEI^{a}}$, $\beta^{MEI^{b}}$, and $\beta^{MEI^{c}}$, we form value-weighted portfolios and obtain factor alphas for each emotion beta decile. Results using models 1, 2, and 3 in Panel A of Table 10 show that β^{MEI} produces positive and significant alphas for all models. The results presented in Table 10, along with those reported in Table 4, indicate that even with alternative specifications, emotion beta remains a significant predictor of stock returns.

4.2 Orthogonalized market emotion indices

In the next set of tests, we examine the performance sensitivity of high-minus-low emotion beta-based trading strategies. In these tests, we estimate stock emotion betas employing 60-month rolling regression similar to that of equation (2), only replacing our original market emotion index with orthogonalized market emotion indices. Similar to Baker and Wurgler (2006), we use different macroeconomic indicators to orthogonalize the market emotion index and estimate emotion beta. We then test the performance of high-minus-low emotion beta-based trading strategy.[25]

Panel B of Table 10 presents the results from using different orthogonalized versions of the market emotion index. A high-minus-low emotion beta strategy generates a positive and significant alpha irrespective of the orthogonalization procedure and factor models used to estimate alphas. These results show that our evidence of emotion-based mispricing is robust.

4.3 Subsample estimates

Next, we investigate if the emotion beta premium is driven by smaller, illiquid, or low-priced stocks. Specifically, we test whether our Long-Short trading strategy generates an alpha for the S&P 500 firms, the largest 1,000 firms based on market capitalization, and 1,000 most liquid firmd based on Amihud's (2002) illiquidity measure. Panel A of Table 11 presents the respective FF5, *q*-factor, BS6, and DHS3 alpha spreads between high-β^{MEI} and low-β^{MEI} portfolio returns. For S&P 500 firms, this spread ranges from 0.68% to 0.80% per month (*t*-statistic from 2.45 to 3.05), 0.51% to 0.61% per month (*t*-statistic from 3.02 to 3.92) for the

[25] The procedure of collecting residual following Baker and Wurgler (2006) may suffer from look-ahead bias. To alleviate those concerns, we run a 24-month rolling regressions to collect residuals to get our three orthogonalized market emotion indices. Our results remain qualitatively similar.

largest 1,000 stocks, and 0.47% to 0.56% per month (*t*-statistic from 2.68 to 3.27) for the 1,000 most liquid firms. These results indicate that emotion premium is not concentrated among small, illiquid, and low-priced firms.

4.4 Subperiod estimates

It is possible that the impact of emotion-based stock beta varies with the business cycle. Investors might be particularly emotional during up or down phases of the economy. If this is the case, then we should only observe significant emotion beta-based trading strategy alphas in up or down, low or high volatility, expansion or recession periods. Alternatively, if investors are continually searching for an emotional 'fix', irrespective of economic conditions, a high-minus-low emotion beta-based trading strategy would earn economically significant alphas in both sub-periods.

We divide the full sample into up and down, low and high volatility, crisis and non-crisis periods. We define up (down) market state by the months in which the CRSP value-weighted index return is greater (lower) than its median value over the full sample period. Similarly, we define high (low) volatility periods by the months in which the value of VIX is greater (lower) than its median value over the full sample period. Our crisis period includes both NBER recessions, the dot.com bubble (October 1998 to September 2002), the Global Financial Crisis (January 2006 to June 2011), and the Covid-19 pandemic (March to April 2020). We report the results in Panel B of Table 11. We find that a high-minus-low emotion beta trading strategy generates economically significant alpha after controlling for well-known asset-pricing factors in up and down, low and high volatile market conditions, and crisis and non-crisis periods alike.

We then examine whether emotion-based alpha is only significant in periods of high or low sentiment. We split stocks based on the median of the Baker and Wurgler (2006) investor sentiment index. High (low) sentiment periods are defined by the months in which the Baker and Wurgler (2006) index is greater (lower) than its median value over the full sample period.

Panel B of Table 11 shows that the high-minus-low trading strategy generates economically significant alphas during both high and low sentiment periods.

Taken together, these results suggest that the impact of investor emotion on asset prices is robust. Investor emotions influence prices during good and bad economic conditions and also during low or high investor sentiment periods. One of the two emotions (anxiety or excitement) plays a role in both positive and negative environments.

4.5 Extreme portfolio alphas

All our portfolio level analysis so far has been based on decile portfolios. In this subsection, we determine whether the high-minus-low trading strategy alpha is robust across different portfolio composition choices. We construct a series of Long-Short portfolios sorted from tercile to decile. Figure 6 displays their extreme portfolio alphas. Each Long-Short portfolio alpha controls for the seven factors: market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ). Figure 6 shows how across all portfolios, a Long-Short investment strategy generates economically and statistically significant alphas. We conclude that our results are not driven by a specific choice for constructing portfolios.

Overall, our robustness checks support our main conjecture that high emotion beta stocks generate high stock returns compared to low emotion beta stocks. Whether we work with alternative measures of emotion beta, orthogonalized market emotion index, different stock subsamples and subperiods, or construct different numbers of stock portfolios, results are very similar. All these robustness tests concur with our main findings that emotion-based sentiment is an important predictor of cross-section of stock returns.

5. Summary and Conclusions

Casual observation of investors in financial markets indicates that emotions are influential in driving their investment decisions. In this paper, we show that the emotional engagement of investors with certain subsets of stocks influence their portfolio decisions. Depending on the strength of this relation, emotion-based sentiment may influence asset prices in those market segments that are emotion sensitive. We focus on the emotions of excitement and anxiety in this paper, and propose a novel method to measure the emotional state of the market.

Using our stock emotion-sensitivity measure, we demonstrate that returns in the market segments with high emotion-sensitivity are predictable. A Long-Short emotion beta-based trading strategy generates an annualized alpha ranging from 6.36% to 9.00% during the 1995-2022 period. This evidence of predictability is robust, more pronounced when arbitrage is costly and mispricing is more prevalent, and extends up to 6 months following the portfolio formation date.

Our evidence of predictability is distinct from other forms of predictability identified in the related literature on investor sentiment. In particular, our emotion-based predictability differs from known sentiment-based predictability. We document return predictability that is incremental over the effects of mood, sentiment, economic/policy uncertainty, and narrative tone-based measures.

Overall, our results establish a link between emotions and market mispricing. In future work, it would be interesting to examine whether variation in emotions influence other market participants and other areas of financial markets. For example, retail and institutional investors may overweight emotion-sensitive firms differently, which would have predictable impact on asset prices in different market sectors. It would also be interesting to investigate how corporate managers respond to emotion-induced mispricing and how sell-side equity analysts are likely to develop emotional relationships with the firms they cover and adjust their forecasts in response to these emotional connections. Related research might also extend the approach taken in this paper to other asset classes and markets.

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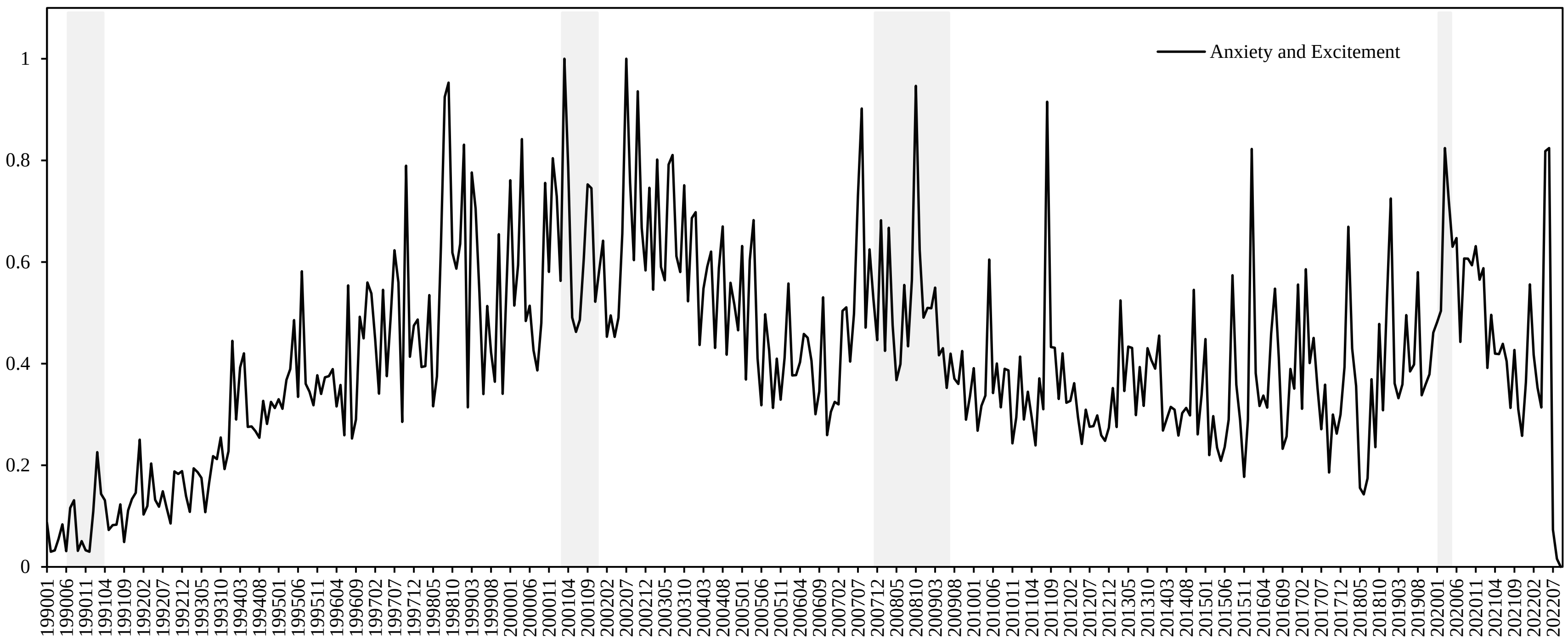


Figure 1: 'Anxiety' and 'Excitement' over time. The figure shows the anxiety and excitement word counts over time. We use news articles over a month to get the monthly word counts for anxiety and excitement. We normalize the word counts to have a value between 0 and 1 for easier interpretation. The shaded areas represent NBER recession periods. The sample period is from January 1990 to September 2022.

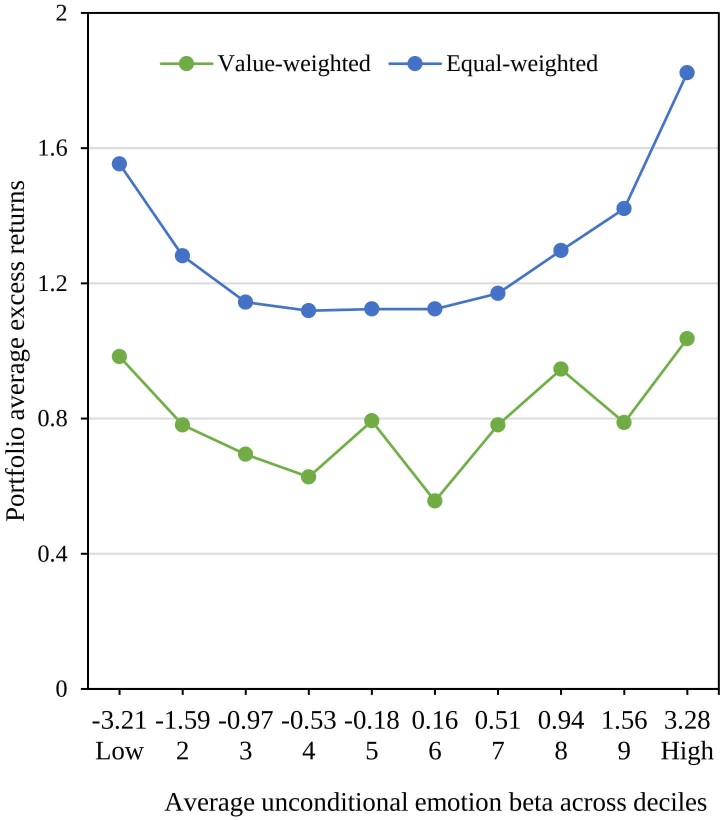


Figure 2: Average excess returns across directional emotion beta portfolios. The figure shows average excess returns across directional emotion beta portfolio deciles. First, we estimate emotion betas following Eq. (2) and then sort them into decile portfolios where L (H) portfolio includes stocks with most negative (positive) emotion betas. Second, we estimate average excess returns for each of the decile portfolios. We report both equal- and value-weighted average excess returns. The estimation period is from January 1995 to September 2022.

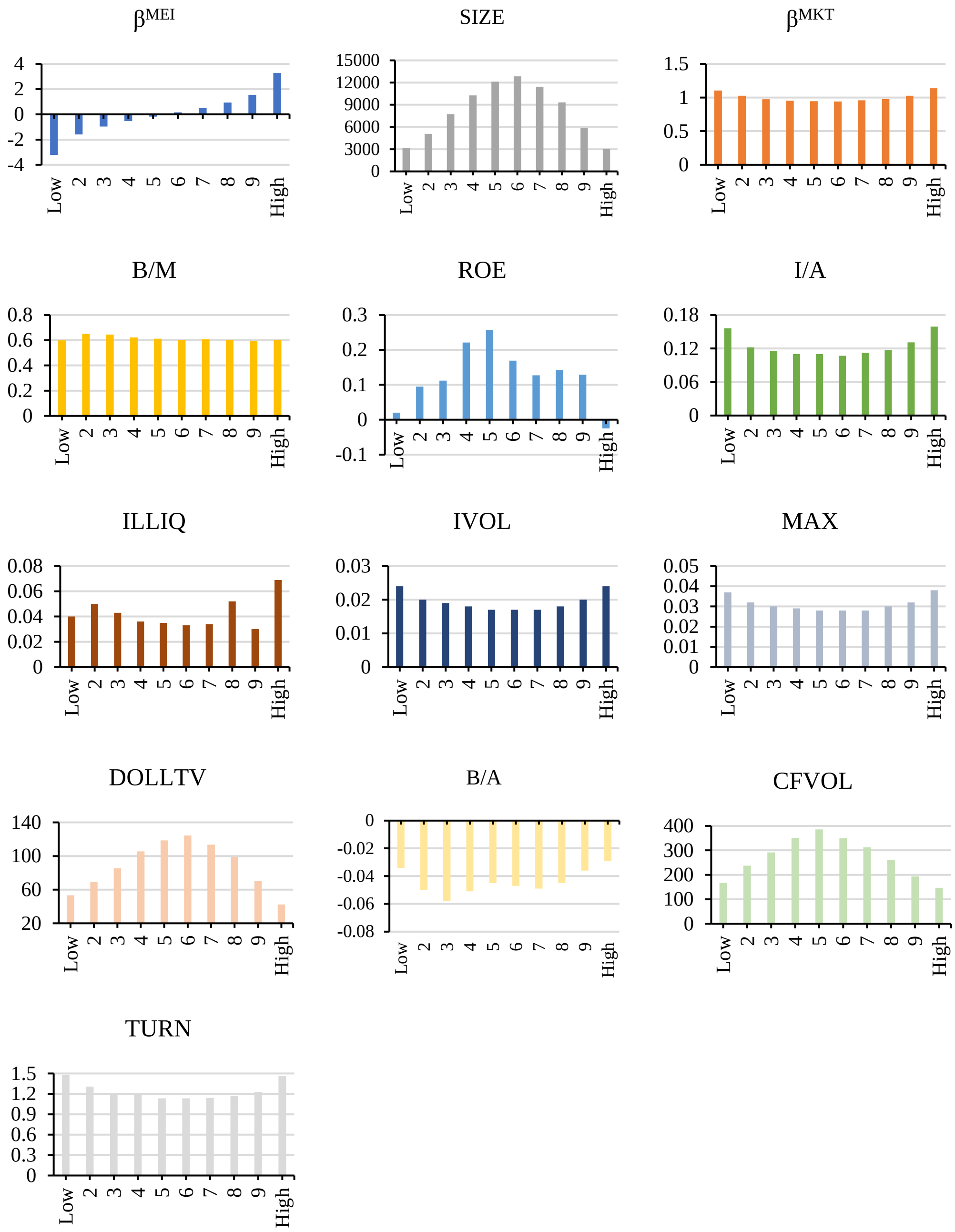
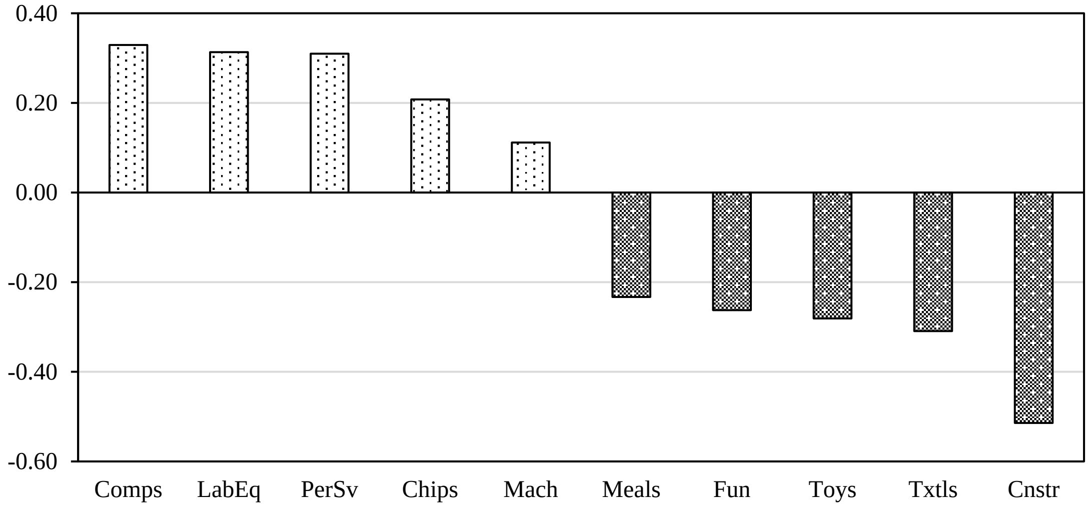


Figure 3: Directional emotion beta-based portfolio characteristics. The figure presents characteristics of directional emotion beta-based portfolio. The characteristics are the average directional emotion beta (β^{MEI*}), market beta (β^{MKT}), SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), profitability (ROE), annual growth of assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), demand for lottery-like stocks (MAX), mispricing (MISP) measured as absolute value of natural logarithm of ratio of market-to-book to median market-to-book ratio, dollar trading volume (DOLLTV) measured as average of volume multiplied by price over the previous 12-months, abnormal trading volume (ABVOL) measured as the ratio of dollar trading volume to average of volume multiplied by price over the previous 12-months, bid-ask (B/A) spreads measured as $2 \times ABS(PRC - (ASK + BID)/2)/PRC$ then taking the average of over the previous 12-months, age (AGE), trading volume (TRDVOL) measured as the average of trading volume over the previous 6-months, and turnover (TURN) average of volume multiplied by price over the previous 12-months across portfolios. The estimation period is from January 1995 to September 2022.

Panel A: Top and bottom five industries with highest and lowest unconditional emotion beta



Panel B: Top and bottom five industries with highest and lowest conditional emotion beta

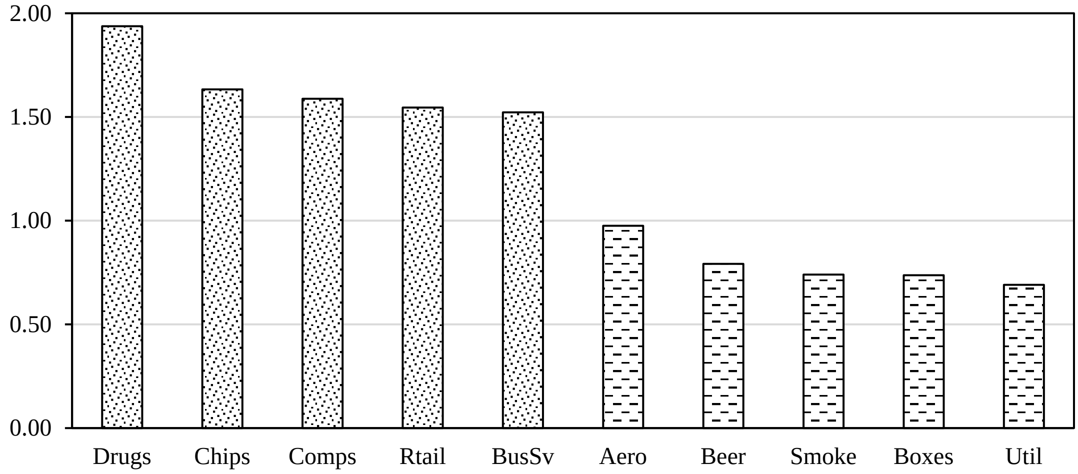


Figure 4: Top and bottom Fama-French industries. The figure shows average emotion beta for the Fama-French 48 industry classification. The industry-level emotion beta is average of all firms in a specific industry. We report the time-series average of unconditional and conditional (absolute value) industry-level emotion betas. Panel A shows the top and bottom five 48 Fama-French industries, based on unconditional emotion beta and Panel provides the equivalent for conditional emotion beta. The estimation period is from January 1995 to September 2022.

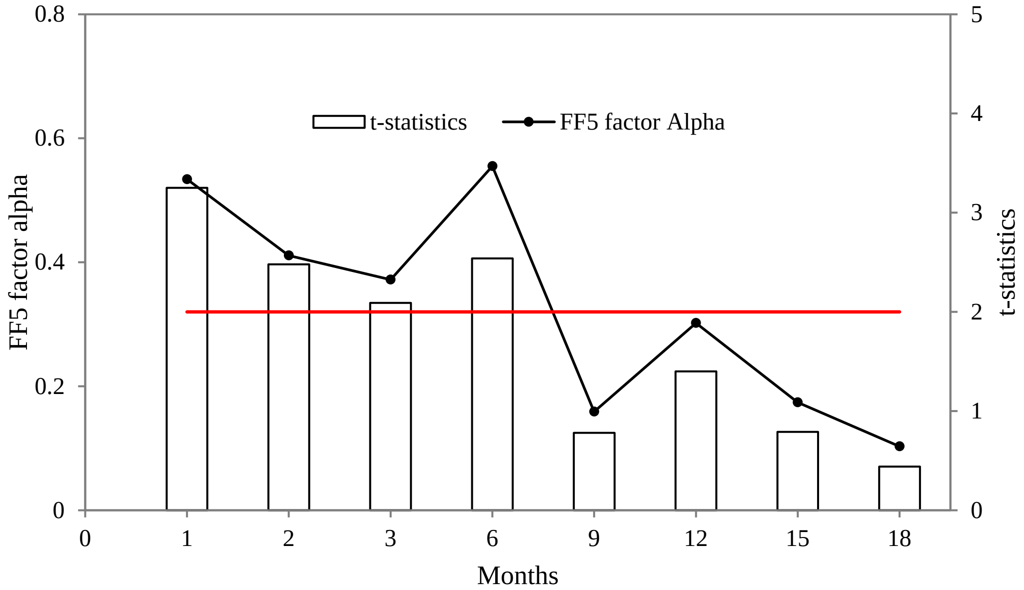


Figure 5: Longevity of alpha. The figure presents a series of Long-Short trading strategy alphas for different portfolios formed on emotion beta (β^{MEI}). For each month, we form portfolios based on emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) β^{MEI} during the previous formation months. We examine the longevity of high-minus-low emotion beta-based trading strategy alphas. We keep on increasing the gap between the portfolio formation and emotion beta portfolio return estimation month. The five-factor alphas are relative to market (MKT), size (SMB), value (HML), operating profitability (RMW), and investment (CMA) factors. The black line indicates 5-factor alphas and columns represent Newey-West *t*-statistics for respective alphas. The red line represents *t*-statistics at 2.00. The estimation period is from January 1995 to September 2022.

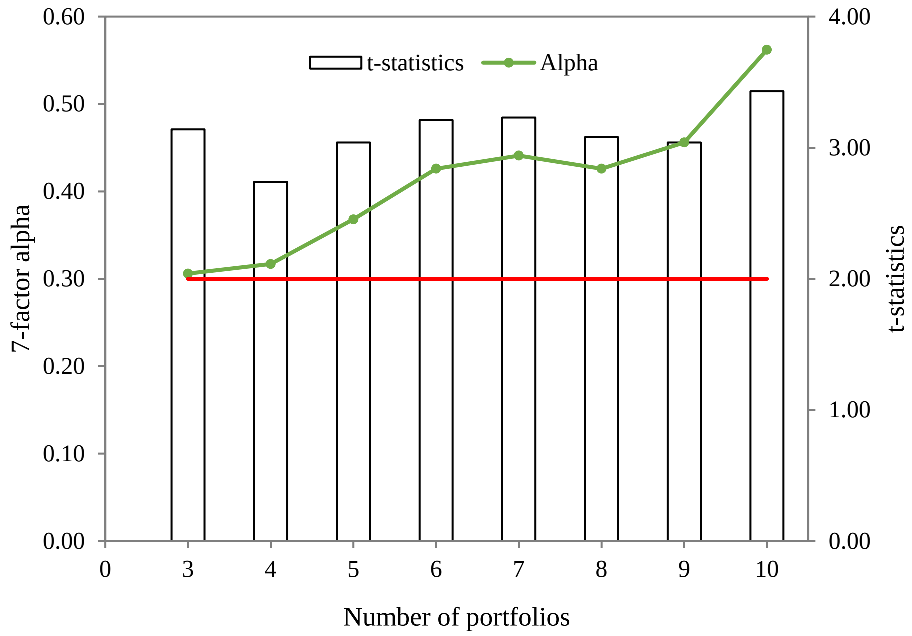


Figure 6: Extreme portfolio alpha. The figure presents a series of emotion beta-based Long-Short trading strategy alphas and their associated *t*-statistics. For each month, we form portfolios ranging from tercile to decile by sorting stocks based on their emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) β^{MEI} during the previous formation months. The seven-factor alphas are relative to market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ) factors. The black line indicates 7-factor alphas and columns represent Newey-West *t*-statistics for respective alphas. The red line represents *t*-statistics at 2.00. The estimation period is from January 1995 to September 2022.

Table 1: Correlations and summary statistics

The table reports correlation between and summary statistics of key variables. Panel A presents correlation analysis between market emotion index (MEI), its orthogonalized variations, volatility, macro-wide sentiment, economic and policy uncertainty, and textual tone measures. Market emotion index is measured as the ratio of total of excitement and anxiety word counts to the total word counts from 21 newspaper articles in a month. We use news articles over a month to get the monthly word counts for excitement and anxiety. Following Baker and Wurgler (2006), we construct three orthogonalized MEIs ($MEI^{\perp}$, $MEI^{\perp\perp}$, and $MEI^{\perp\perp\perp}$) by collecting residuals from regressions of MEI on (i) macroeconomy related indicators (growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions); (ii) macro uncertainty and tone measures (VIX, economic uncertainty index (Jurado, Ludvigson, and, Ng, 2015, UNC), economic policy uncertainty index (Baker, Bloom, and Davis, 2016, EPU), investor sentiment (Baker and Wurgler, 2006, BWSENT), University of Michigan's Consumer Confidence Index, and two positive-/negative-based tone measures (Loughran and McDonald, 2011, LN; Henry, 2008, HN); and (iii) a combination of variables listed in (i) and (ii). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries, respectively. Panel B shows the correlation between firm-specific emotion beta and other firm characteristics. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and asset pricing factors—market, size, value, momentum, liquidity, investment, profitability, finance, post earnings announcement drift, betting against beta. We then take absolute value of emotion beta. Panel C reports the mean, standard deviation, 25th percentile, median, and 75th percentile of the market emotion index (MEI), absolute emotion beta (β^{MEI}), directional emotion sensitivity (β^{MEI*}), and other firm characteristics. Firm characteristics are SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of assets (I/A), operating profitability (ROE), and demand for lottery-like stocks (MAX). The sample period is from January 1990 to September 2022.

Panel A: Correlation between MEI and other measures

	MEI	$MEI^{\perp}$	$MEI^{\perp\perp}$	$MEI^{\perp\perp\perp}$	VIX	BWSENT	UMCCI	UNC	EPU	LM	HN
MEI	1	0.967	0.978	0.963	0.004	0.017	0.039	-0.100	-0.002	0.086	-0.036
$MEI^{\perp}$		1	0.959	0.996	0.064	0.072	-0.051	-0.034	0.009	-0.018	-0.086

Panel B: Correlation between emotion beta and firm-specific risk factors and characteristics

	β^{MKT}	β^{VIX}	SIZE	B/M	MOM	REV	ILLIQ	IVOL	I/A	ROE	MAX
β^{MEI}	0.142	0.014	-0.080	-0.017	0.092	0.022	0.006	0.199	0.050	-0.019	0.188

Panel C: Summary statistics

	MEI	β^{MEI*}	β^{MEI}	SIZE	B/M	MOM	REV	ILLIQ	IVOL	I/A	ROE	MAX
Mean	0.042	-0.004	1.325	7734.266	0.607	0.186	0.011	0.041	0.019	0.126	0.121	0.031
Standard deviation	0.005	1.895	1.356	37227.430	0.760	0.695	0.134	1.119	0.013	0.413	3.764	0.021
25th percentile	0.039	-0.945	0.419	303.964	0.275	-0.107	-0.053	0.000	0.011	-0.012	0.035	0.018
Median	0.042	-0.008	0.935	1050.741	0.474	0.100	0.007	0.000	0.016	0.059	0.104	0.026
75th percentile	0.045	0.925	1.789	3849.032	0.762	0.341	0.069	0.002	0.024	0.160	0.183	0.039

Table 2: Fama-MacBeth cross-sectional regression estimates

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion beta (β^{MEI}) and a set of lagged control variables using the Fama-MacBeth method. The control variables are market beta (β^{MKT}), volatility beta (β^{VIX}), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). We standardize all explanatory variables for easier interpretation. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported below the estimates. The estimation period is from January 1995 to September 2022.

	Without industry effects						With industry effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β^{MEI}	0.254	0.253	0.239	0.231	0.207	0.094	0.211	0.213	0.211	0.198	0.184	0.091
	(3.40)	(3.63)	(3.68)	(3.74)	(3.54)	(2.06)	(3.63)	(3.86)	(3.84)	(4.01)	(3.94)	(2.30)
β^{MKT}		-0.278	0.078	0.042	0.016	0.046		0.042	0.040	0.030	0.009	0.045
		(-1.61)	(1.18)	(0.69)	(0.27)	(0.85)		(0.80)	(0.75)	(0.58)	(0.19)	(0.94)
β^{VIX}			-0.111	-0.300	-0.360	-0.111			-0.231	-0.266	-0.324	-0.102
			(-2.31)	(-1.84)	(-2.12)	(-2.76)			(-1.60)	(-1.87)	(-2.18)	(-2.86)
SIZE				-0.201	-0.198	-0.112				-0.207	-0.201	-0.115
				(-2.97)	(-2.99)	(-1.93)				(-3.02)	(-3.04)	(-2.03)
B/M				-0.310	-0.264	-0.385				-0.256	-0.220	-0.360
				(-3.62)	(-3.09)	(-4.71)				(-3.42)	(-2.88)	(-4.85)
MOM				-0.136	-0.258	-0.305				-0.147	-0.260	-0.312
				(-0.99)	(-1.82)	(-2.23)				(-1.20)	(-2.03)	(-2.51)
REV					-2.81	-0.217					-0.293	-0.230
					(-4.38)	(-3.61)					(-4.90)	(-4.06)
I/A					0.364	0.436					0.337	0.416
					(7.77)	(10.02)					(7.91)	(10.49)
ROE					0.494	0.917					0.476	0.876
					(4.22)	(3.99)					(2.21)	(4.05)
ILLIQ						0.799						0.779
						(2.39)						(2.69)
IVOL						0.776						0.798
						(8.66)						(9.67)
MAX						-0.676						-0.725
						(-5.94)						(-7.21)
Intercept	1.325	1.325	1.325	1.239	1.206	1.067	1.284	1.191	1.382	1.095	1.300	0.881
	(4.49)	(4.53)	(4.53)	(4.24)	(4.22)	(3.84)	(3.52)	(3.04)	(3.52)	(2.71)	(3.40)	(2.46)
Adj. R-squared	0.64%	1.88%	1.91%	3.61%	4.70%	6.08%	5.15%	5.69%	6.01%	7.35%	8.27%	9.39%
N months	333	333	333	333	333	333	333	333	333	333	333	333

Table 3: Characteristics of emotion beta sorted portfolios

The table reports the characteristics of emotion beta portfolios. For each month, we form decile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the previous month. Columns 1 to 10 present the average emotion beta (β^{MEI}), market beta (β^{MKT}), SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), profitability (ROE), annual growth of assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and demand for lottery-like stocks (MAX). The last column presents the difference between high and low portfolios along with the *t*-statistics computed after adjusting for Newey-West (1987) standard errors. The estimation period is from January 1995 to September 2022.

	Portfolios										
	Low	2	3	4	5	6	7	8	9	High	High-Low
β^{MEI}	0.085	0.255	0.431	0.619	0.832	1.076	1.376	1.773	2.385	4.130	4.045
											(36.95)
β^{MKT}	0.946	0.945	0.952	0.957	0.966	0.984	1.015	1.039	1.079	1.162	0.217
											(15.85)
SIZE	12,866.900	12,005.200	11,495.860	10,411.870	9,205.773	7,852.236	6,165.113	4,784.533	3,797.324	2,264.416	-10,602.480
											(-9.10)
B/M	0.609	0.609	0.606	0.614	0.629	0.626	0.627	0.618	0.614	0.588	-0.021
											(-1.28)
ROE	0.262	0.169	0.191	0.147	0.128	0.134	0.109	0.119	0.057	-0.068	-0.330
											(-3.88)
I/A	0.109	0.107	0.113	0.110	0.114	0.118	0.125	0.129	0.141	0.171	0.062
											(7.69)
IVOL	0.017	0.017	0.017	0.018	0.018	0.019	0.019	0.021	0.022	0.026	0.009
											(26.89)
ILLIQ	0.034	0.036	0.031	0.038	0.046	0.049	0.039	0.039	0.034	0.076	0.042
											(2.46)
MAX	0.028	0.028	0.028	0.029	0.029	0.030	0.031	0.033	0.036	0.041	0.013
											(22.34)

Table 4: Performance of emotion beta sorted portfolios

The table presents portfolio average excess returns across different return adjustment models and unconditional factor model alphas. For each month, we form decile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the previous month. In column 1 and 2, we present the value-weighted average excess and Fama-French (1997) 48 industry-adjusted returns. In columns 3 to 6, we present emotion beta-based portfolio alphas (α_{FF5}, α_q, α_{BS6}, and α_{DHS3}) controlling for Fama and French (2015, FF5) 5-factors, Hou, Xue, Zhang (2015, *q*-factor) 4-factors, Barillas and Shanken (2018, BS6) 6-factors, and Daniel, Hirshleifer, and Sun (2020, DHS3) 3-factors for value-weighted portfolios. The last row presents results for high-minus-low portfolios. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

Portfolios	RET-RF	Industry-adjusted return	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	0.613	-0.387	-0.168	-0.109	-0.089	-0.092
	(2.52)	(-1.32)	(-2.11)	(-1.44)	(-1.17)	(-1.02)
2	0.852	-0.128	0.065	0.151	0.142	0.108
	(4.07)	(-0.43)	(0.79)	(1.80)	(1.65)	(1.32)
3	0.744	-0.173	0.036	0.065	0.075	0.055
	(3.08)	(-0.63)	(0.35)	(0.64)	(0.71)	(0.53)
4	0.538	-0.439	-0.197	-0.177	-0.167	-0.101
	(2.02)	(-1.50)	(-1.58)	(-1.48)	(-1.38)	(-0.83)
5	0.859	-0.147	0.147	0.165	0.155	0.138
	(3.10)	(-0.63)	(1.27)	(1.55)	(1.42)	(1.21)
6	0.928	-0.046	0.124	0.196	0.207	0.270
	(3.93)	(-0.17)	(1.20)	(1.82)	(1.93)	(2.28)
7	0.722	-0.239	-0.074	-0.056	-0.066	0.225
	(2.72)	(-1.08)	(-0.62)	(-0.46)	(-0.53)	(0.19)
8	0.916	0.043	0.189	0.226	0.227	0.281
	(3.13)	(0.19)	(1.42)	(1.59)	(1.58)	(1.71)
9	0.816	0.080	0.174	0.224	0.240	0.258
	(2.41)	(0.37)	(1.25)	(1.46)	(1.60)	(1.78)
High	1.196	0.267	0.366	0.642	0.633	0.618
	(2.83)	(1.24)	(2.51)	(3.79)	(4.03)	(3.54)
High-Low	**0.583**	**0.654**	**0.534**	**0.751**	**0.722**	**0.709**
	(2.04)	**(2.68)**	**(3.25)**	**(4.24)**	**(4.32)**	**(3.37)**

Table 5: Emotion beta alphas across limits to arbitrage and mispricing subsamples

The table reports emotion beta-based trading strategy alphas across different limits to arbitrage and mispricing subsamples. We employ five proxies for limits to arbitrage: i) idiosyncratic volatility; ii) dollar trading volume; iii) bid-ask spread; iv) cash flow volatility; and v) turnover. We employ five mispricing proxies: i) net stock issuance; ii) composite equity issuance; iii) asset growth; iv) momentum; and v) return on assets. For each month, we divide our sample in high and low bins based on the median values of these proxies. We, then, form decile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the previous month. We present only the high minus low portfolios alphas across four different factor models – i) Fama and French (2015, FF5); ii) Hou, Xue, Zhang (2015, q-factor); iii) Barillas and Shanken (2018, BS6); and iv) Daniel, Hirshleifer, and Sun (2020, DHS3). Following Ang et al. (2006), we measure idiosyncratic volatility. We estimate dollar trading volume as the average of volume multiplied by price over the previous 12-months. We then take its reciprocal for easier interpretation. The bid-ask (B/A) spread is $2 \times ABS(PRC - (ASK + BID)/2)/PRC$ then we take the average of over the previous 12-months. Cash flow volatility is the standard deviation of cash flow from operations over the previous 5 years. Turnover is average of volume multiplied by price over the previous 12-months across portfolios. We then take its reciprocal for easier interpretation. Following Stambaugh and Yuan (2017), we measure net stock issuance as the annual log change in split-adjusted shares outstanding where split-adjusted shares equal shares outstanding (CSHO) times the adjustment factor (ADJEX_C); composite equity issuance is the growth in the firm's total market value of equity minus the stock's rate of return. We then subtract the 12-month cumulative return from the 12-month growth in equity market capitalization; asset growth is the annual growth rate of total assets; momentum is cumulative returns from month $t - 12$ to month $t - 2$; and return on assets is the ratio of earnings to lagged assets. The t-statistics are computed after adjusting for Newey-West (1987) standard errors. The estimation period is from January 1995 to September 2022.

Panel A: Portfolio alphas across limits to arbitrage subsamples.

	Idiosyncratic Volatility		1/Dollar Trading Volume		Bid-Ask Spread		Cash Flow Volatility		1/Turnover	
	High	Low	High	Low	High	Low	High	Low	High	Low
α_{FF5}	0.782	0.548	0.696	0.412	1.180	0.262	0.699	-0.054	0.762	-0.384
	(2.60)	(2.26)	(3.81)	(2.45)	(3.55)	(1.23)	(3.73)	(-0.29)	(2.87)	(-1.69)
α_q	0.865	0.411	0.754	0.508	1.185	0.447	0.690	-0.137	0.807	-0.152
	(2.92)	(1.77)	(3.75)	(2.85)	(3.16)	(1.94)	(3.45)	(-0.66)	(3.03)	(-0.60)
α_{BS6}	0.824	0.406	0.772	0.493	1.178	0.447	0.712	-0.116	0.775	-0.153
	(2.83)	(1.91)	(4.09)	(2.81)	(3.36)	(1.95)	(3.44)	(-0.59)	(2.75)	(-0.68)
α_{DHS3}	0.967	0.435	0.791	0.449	1.199	0.388	0.698	0.037	0.694	-0.091
	(3.01)	(2.15)	(4.07)	(2.06)	(2.97)	(1.59)	(3.12)	(0.19)	(2.26)	(-0.37)

Panel B: Portfolio alphas across mispricing subsamples.

	Net Stock Issuance		Composite Equity Issuance		Asset Growth		Momentum		Return on Assets	
	High	Low	High	Low	High	Low	High	Low	High	Low
α_{FF5}	0.511	-0.217	1.001	0.029	0.732	0.018	0.413	0.187	0.458	0.585
	(2.31)	(-0.71)	(3.06)	(0.10)	(3.08)	(0.09)	(1.97)	(0.82)	(2.30)	(1.85)
α_q	0.589	-0.211	1.133	-0.092	0.978	0.143	0.698	0.295	0.408	0.791
	(2.41)	(-0.71)	(3.38)	(-0.27)	(4.00)	(0.68)	(2.51)	(1.15)	(1.92)	(1.97)
α_{BS6}	0.573	-0.210	1.099	-0.056	0.929	0.170	0.676	0.285	0.412	0.757
	(2.56)	(-0.71)	(3.60)	(-0.18)	(3.83)	(0.82)	(2.36)	(1.16)	(1.93)	(2.29)
α_{DHS3}	0.790	-0.149	1.118	0.204	0.948	0.149	0.809	0.314	0.546	0.794
	(3.02)	(-0.46)	(3.26)	(0.67)	(3.28)	(0.60)	(2.40)	(1.15)	(2.42)	(2.22)

Table 6: Emotion beta sorted portfolios: conditional factor model estimates

The table presents portfolio alphas based on conditional factor models. For each month, we form decile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the previous month. The table present value-weighted portfolio alphas, after considering for Fama-French six factors, Pastor and Stambaugh's (2003) liquidity factor and time-varying U.S. systematic risk factors. The Fama-French factors include the market, size, value, momentum, profitability, and investment factors. The time-varying U.S. systematic risk factors are (i) the NBER recession indicator which takes the value of 1 during recession periods and 0 otherwise; (ii) alternatively, we use prolonged recession period (extreme market conditions, EXTMKT) for the dot.com bubble (October 1998 to September 2002) and Global Financial Crisis (January 2006 to June 2011); (iii) the *cay* residual of Lettau and Ludvigson (2001) which is available up to September 2019; (iv) the paper bill spread which is the difference between commercial paper rate and federal funds rate; (v) the term spread which is the difference between 10-year treasury bond yield and T-bills maturing in 3 months; and (vi) the default spread which is the difference between the yield on BAA- and AAA-rated corporate bonds. Each individual column controls for Fama-French factors (MKT, SMB, HML, MOM, RMW, CMA), LIQ factor, and their interaction with each of the U.S. systematic risk factors. The last two columns include interaction with all the time-varying U.S. systematic risk factors with Fama-French and LIQ factors at the same time. The last row presents the difference between high and low portfolio alphas. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

Portfolios	$\alpha_{FF6+LIQ+REC}$	$\alpha_{FF6+LIQ+EXTMKT}$	$\alpha_{FF6+LIQ+cay}$	$\alpha_{FF6+LIQ+pspd}$	$\alpha_{FF6+LIQ+tspd}$	$\alpha_{FF6+LIQ+dspd}$	α_{all}	$\alpha_{all\ with\ EXTMKT}$
Low	-0.079	-0.136	-0.099	-0.076	-0.127	-0.099	0.003	0.029
	(-0.88)	(-1.61)	(-1.05)	(-0.97)	(-1.46)	(-1.22)	(0.03)	(0.31)
2	0.036	0.052	-0.002	0.036	0.021	0.025	0.024	0.005
	(0.39)	(0.57)	(-0.03)	(0.40)	(0.24)	(0.28)	(0.23)	(0.04)
3	0.022	-0.012	0.027	-0.020	0.027	0.012	0.027	-0.023
	(0.22)	(-0.12)	(0.27)	(-0.20)	(0.29)	(0.11)	(0.24)	(-0.22)
4	-0.145	-0.229	-0.225	-0.199	-0.154	-0.169	-0.196	-0.288
	(-1.20)	(-1.73)	(-1.62)	(-1.56)	(-1.36)	(-1.33)	(-1.34)	(-1.82)
5	0.151	0.173	0.037	0.103	0.125	0.132	0.027	0.083
	(1.18)	(1.51)	(0.30)	(0.86)	(1.01)	(1.02)	(0.19)	(0.56)
6	0.134	0.128	0.122	0.139	0.149	0.126	0.173	0.182
	(1.11)	(1.28)	(1.02)	(1.37)	(1.27)	(1.08)	(1.37)	(1.48)
7	-0.007	0.021	-0.112	-0.043	-0.020	-0.045	0.013	0.058
	(-0.05)	(0.18)	(-0.86)	(-0.34)	(-0.17)	(-0.34)	(0.09)	(0.38)
8	0.175	0.149	0.293	0.184	0.214	0.168	0.266	0.265
	(1.18)	(1.07)	(2.15)	(1.32)	(1.48)	(1.16)	(1.80)	(1.69)
9	0.262	0.178	0.267	0.228	0.305	0.239	0.225	0.220
	(1.92)	(1.24)	(1.87)	(1.76)	(2.29)	(1.67)	(1.60)	(1.49)
High	0.399	0.419	0.431	0.343	0.441	0.431	0.428	0.468
	(2.48)	(2.75)	(2.90)	(2.17)	(2.95)	(2.81)	(2.37)	(2.59)
High-Low	**0.477**	**0.555**	**0.531**	**0.420**	**0.568**	**0.630**	**0.425**	**0.439**
	(2.72)	**(3.35)**	**(2.98)**	**(2.58)**	**(3.40)**	**(3.16)**	**(2.20)**	**(2.18)**

Table 7: Persistence in emotion beta

The table presents results on the persistence of emotion beta. We examine the persistence of emotion beta (β^{MEI}) by running firm-level cross-sectional regressions of β^{MEI} on lagged β^{MEI} and lagged cross-sectional control variables. The first row reports average slope coefficients of univariate Fama-MacBeth regressions of 12-months to 60-months β^{MEI} on lagged β^{MEI}. The last row presents the average slope coefficients after controlling for lagged variables: the market beta (β^{MKT}), market capitalization (SIZE), volatility beta (β^{VIX}), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth in book assets (I/A), operating profitability (ROE), and lottery demand (MAX). All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

n-year-ahead β^{MEI}	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
Univariate predictive regressions	0.790	0.476	0.316	0.202	0.138
	(36.78)	(26.09)	(20.47)	(17.24)	(15.49)
Adj. R-squared	37.92%	16.81%	9.47%	5.84%	4.40%
N months	322	310	298	286	274
Controlling for lagged variables	0.741	0.401	0.242	0.129	0.077
	(35.71)	(23.16)	(17.53)	(13.30)	(10.19)
Adj. R-squared	40.04%	20.63%	14.65%	11.84%	9.37%
N months	322	310	298	286	274

Table 8: Fama-MacBeth regression estimates using mood, sentiment, uncertainty, and tone betas

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion, mood, sentiment, uncertainty, and tone betas along with a set of lagged control variables (used in Table 2) using Fama-MacBeth methodology. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and a set of factors described in equation (2). Then, we take the absolute value of β^{MEI}. The mood beta (β^{Mood}) of Hirshleifer et al. (2020) is computed by running a 5-year rolling regression of excess stock returns on equal-weighted CRSP excess returns during prespecified and realized high and low mood months. Prespecified high mod months are January and March, and low mood months are September and October. The realized extreme positive and negative mood periods are identified using the top and bottom two months ranked based on the equal-weighted CRSP excess returns realized in a given year. The sentiment beta (β^{SENT}) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index and a set of factors listed in equation (2). We generate the consumer confidence beta (β^{UMCCI}) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and a set of factors described in equation (2). Following Bali et al. (2017), we compute the uncertainty beta (β^{UNC}) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and a set of factors described in equation (2). We estimate the economic policy uncertainty beta (β^{EPU}) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and a set of factors listed in equation (2). We derive two tone betas (β^{LM} and β^{HN}) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and a set of factors described in equation (2). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries respectively. For brevity, we do not report the intercepts and coefficients of lagged control variables. We standardize all explanatory variables for easier interpretation. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported below the estimates. The estimation period is from January 1995 to September 2022.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β^{MEI}	0.951	0.119	0.095	0.091	0.089	0.094	0.097	0.089	0.864
	(2.41)	(2.50)	(2.42)	(2.31)	(2.26)	(2.34)	(2.49)	(2.38)	(3.08)
β^{Mood}	0.297								0.316
	(0.63)								(0.68)
β^{SENT}		-0.172						0.048	-0.284
		(-0.94)						(0.87)	(-1.11)
β^{UMCCI}			-0.034					0.001	-0.620
			(-0.87)					(0.01)	(-1.41)
β^{UNC}				-0.005				0.062	-0.354
				(-0.13)				(0.76)	(-0.78)
β^{EPU}					0.053			0.084	-0.072
					(1.11)			(1.19)	(-0.12)
β^{LM}						0.031		0.186	0.261
						(0.74)		(1.28)	(0.49)
β^{HN}							-0.003	-0.038	-0.002
							(-0.07)	(-0.37)	(-0.01)
Firm controls & risk factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	27.04%	9.76%	9.54%	9.50%	9.53%	9.55%	9.55%	10.45%	28.86%
N months	185	333	333	333	333	333	333	333	185

Table 9: Emotion beta estimates for bivariate sorted portfolios

The table shows results from bivariate sorts. First, stocks are first sorted into deciles based on a firm characteristic, and then within each characteristic decile stocks are further sorted into deciles based on emotion beta (β^{MEI}). For each emotion beta decile, we average alphas across the ten characteristic groups. The firm characteristics are market capitalization (SIZE), market beta (β^{MKT}), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), and cash flow volatility (CFVOL). We report value-weighted seven-factor alphas (in percentage) relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

Portfolios	SIZE	β^{MKT}	ILLIQ	IVOL	CFVOL
Low	-0.205	-0.156	-0.213	-0.227	-0.155
	(-1.84)	(-1.87)	(-2.02)	(-2.33)	(-1.67)
2	0.146	0.002	0.051	0.068	-0.009
	(1.52)	(0.02)	(0.55)	(0.81)	(-0.10)
3	-0.164	-0.154	-0.054	-0.080	-0.111
	(-1.51)	(-1.86)	(-0.53)	(-0.75)	(-1.27)
4	0.070	-0.005	-0.070	0.018	-0.025
	(0.73)	(-0.04)	(-0.58)	(0.21)	(-0.19)
5	-0.144	0.001	0.004	0.004	0.004
	(-1.07)	(0.01)	(0.04)	(0.04)	(0.04)
6	0.116	-0.013	0.018	0.080	0.090
	(0.96)	(-0.13)	(0.15)	(0.73)	(0.96)
7	0.097	0.152	-0.024	-0.030	-0.036
	(0.90)	(1.21)	(-0.22)	(-0.28)	(-0.27)
8	-0.003	0.148	0.166	0.387	0.052
	(-0.02)	(1.05)	(1.37)	(2.96)	(0.37)
9	0.141	0.217	0.050	-0.091	0.135
	(1.04)	(1.49)	(0.35)	(-0.63)	(0.97)
High	0.238	0.237	0.389	0.346	0.365
	(1.49)	(1.34)	(2.78)	(2.42)	(1.93)
High-Low	**0.442**	**0.394**	**0.602**	**0.573**	**0.520**
	(2.48)	**(2.01)**	**(3.44)**	**(3.41)**	**(2.51)**

Table 10: Alpha estimates for emotion beta sorted portfolios: Alternative models

The table reports alpha estimates for alternative measures of conditional emotion beta and market emotion index measures. In Panel A, for each month, we sort stocks into decile portfolios based on conditional emotion beta (β^{MEI}), estimated using alternative models:

Model 1: $R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^a} MEI_t + \beta_{i,t}^{MKT} MKT_t + \varepsilon_{i,t}$,

Model 2: $R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^b} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \varepsilon_{i,t}$,

Model 3: $R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^c} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{MOM} MOM_t + \varepsilon_{i,t}$,

In Panel B, following Baker and Wurgler (2006), we construct three orthogonalized MEIs ($MEI^{\perp}$, $MEI^{\perp\perp}$, and $MEI^{\perp\perp\perp}$) by collecting residuals from regressions of MEI on (i) macroeconomy related indicators (growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions); (ii) macro uncertainty and tone measures (economic uncertainty index (Jurado et al., 2015), economic policy uncertainty index (Baker et al., 2016), investor sentiment (Baker and Wurgler, 2006), University of Michigan's Consumer Confidence Index, and two positive-/negative-based tone measures (Loughran and McDonald, 2011; Henry, 2008); and (iii) a combination of variables listed in (i) and (ii). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries, respectively. For each month, we form decile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where decile 1 (10) contains stocks with the lowest (highest) β^{MEI} during the previous month. The last row presents the differences between high and low β^{MEI} portfolio returns. We estimate value-weighted portfolio alphas controlling for Fama and French (2015, FF5) 5-factor, Hou, Xue, Zhang (2015, *q*-factor) 4-factor, Barillas and Shanken (2018, BS6) 6-factor, and Daniel, Hirshleifer, and Sun (2020, DHS3) 3-factor models. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

Panel A: Alpha estimates for alternative models

Portfolios	Model 1				Model 2				Model 3			
	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	-0.051	-0.025	-0.014	-0.050	-0.193	-0.139	-0.131	-0.139	-0.146	-0.103	-0.102	-0.112
	(-0.83)	(-0.39)	(-0.21)	(-0.68)	(-2.26)	(-1.67)	(-1.58)	(-1.70)	(-1.72)	(-1.28)	(-1.30)	(-1.32)
High	0.414	0.636	0.639	0.660	0.256	0.526	0.514	0.541	0.268	0.539	0.514	0.521
	(2.30)	(3.08)	(3.28)	(3.11)	(1.57)	(2.79)	(2.97)	(3.02)	(1.53)	(2.72)	(3.00)	(2.66)
High-Low	**0.466**	**0.661**	**0.653**	**0.710**	**0.449**	**0.665**	**0.645**	**0.680**	**0.414**	**0.641**	**0.616**	**0.633**
	(2.39)	**(2.97)**	**(3.03)**	**(3.12)**	**(2.36)**	**(3.01)**	**(3.26)**	**(3.19)**	**(2.13)**	**(2.88)**	**(3.34)**	**(2.83)**

Panel B: Alpha estimates with orthogonalized MEI

Portfolios	$MEI^{\perp}$				$MEI^{\perp\perp}$				$MEI^{\perp\perp\perp}$			
	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	-0.127	-0.040	-0.039	-0.018	-0.141	-0.048	-0.035	-0.060	-0.102	-0.053	-0.039	-0.060
	(-1.35)	(-0.45)	(-0.42)	(-0.19)	(-1.62)	(-0.60)	(-0.43)	(-0.68)	(-1.14)	(-0.64)	(-0.45)	(-0.66)
High	0.197	0.437	0.447	0.455	0.372	0.484	0.489	0.558	0.161	0.412	0.426	0.414
	(1.37)	(2.61)	(2.89)	(2.76)	(2.30)	(2.89)	(2.81)	(3.15)	(1.15)	(2.28)	(2.58)	(2.37)
High-Low	**0.33**	**0.477**	**0.486**	**0.473**	**0.513**	**0.532**	**0.524**	**0.618**	**0.263**	**0.464**	**0.465**	**0.474**
	(2.05)	**(2.68)**	**(2.95)**	**(2.44)**	**(2.68)**	**(2.80)**	**(2.61)**	**(2.77)**	**(1.75)**	**(2.64)**	**(2.85)**	**(2.47)**

Table 11: Additional analysis: Alpha estimates for different subsamples

The table reports emotion premium across different subsample of stocks. In Panel A, we estimate alphas for stocks included in the S&P 500 index, largest 1000 stocks, and based on Amihud's (2002) illiquidity measure the most liquid 1000 stocks. For each month, we form decile portfolios by sorting the subsampled stocks based on their absolute emotion beta (β^{MEI}), where decile 1(10) contains stocks with the lowest (highest) β^{MEI} during the previous month. Panel B reports the results from univariate portfolios of stocks sorted on emotion beta over different subperiods defined by crisis and non-crisis periods, different states of sentiment, market condition, volatility, economic uncertainty, and economic policy uncertainty. The crisis periods include both NBER recessions and broadly defined dot.com bubble (October 1998 to September 2002) and Global Financial Crisis (January 2006 to June 2011) periods. The second two subperiods are high and low sentiment periods, where high (low) sentiment periods are defined by months in which Baker and Wurgler (2006) investor sentiment index is greater (lower) than its median value over the full sample period. The third two subperiods are up and down market, where up (down) market is defined by months in which CRSP value-weighted index return is greater (lower) than its median value over the full sample period. The fourth two subperiods are high and low market volatility, where high (low) market volatility is defined by months in which the value of VIX is greater (lower) than its median value over the full sample period. The fifth two subperiods are high and low economic uncertainty, where high (low) economic uncertainty is defined by months in which the value of economic uncertainty of Jurado et al. (2015) is greater (lower) than its median value over the full sample period. The final two subperiods are high and low economic policy uncertainty, where high (low) economic policy uncertainty is defined by months in which the value of economic policy uncertainty of Baker et al. (2016) is greater (lower) than its median value over the full sample period. For each month in the corresponding subperiod, both panels present the next-month value-weighted Fama and French (2015, FF5) 5-factor, Hou, Xue, Zhang (2015, *q*-factor) 4-factor, Barillas and Shanken (2018, BS6) 6-factor, and Daniel, Hirshleifer, and Sun (2020, DHS3) 3-factor alphas of β^{MEI}-sorted decile portfolios. The last row in both the panel presents the alpha spreads for the hedge portfolio that is long in the decile of stocks with the highest β^{MEI} and short in the decile of stocks with the lowest β^{MEI}. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to September 2022.

Panel A: Emotion premium across different stock subsamples

	S&P 500				Largest 1000				Liquid 1000			
Portfolios	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	-0.379	-0.326	-0.306	-0.310	-0.172	-0.010	-0.086	-0.101	-0.181	-0.111	-0.096	-0.116
	(-3.09)	(-2.53)	(-2.27)	(-2.15)	(-2.00)	(-1.22)	(-1.04)	(-1.08)	(-2.14)	(-1.33)	(-1.15)	(-1.20)
High	0.373	0.471	0.484	0.370	0.341	0.513	0.519	0.503	0.286	0.442	0.454	0.441
	(1.98)	(2.27)	(2.36)	(1.93)	(2.75)	(3.56)	(3.72)	(3.16)	(2.12)	(2.76)	(2.98)	(2.69)
High-Low	**0.752**	**0.796**	**0.790**	**0.680**	**0.513**	**0.613**	**0.605**	**0.604**	**0.467**	**0.554**	**0.550**	**0.557**
	(3.05)	**(3.00)**	**(3.04)**	**(2.45)**	**(3.42)**	**(3.92)**	**(3.92)**	**(3.02)**	**(2.95)**	**(3.25)**	**(3.27)**	**(2.68)**

Panel B: Subperiod analysis

	Market condition								Volatility							
	Up market				Down market				Low				High			
	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	-0.133	-0.113	-0.078	-0.120	-0.196	-0.088	-0.079	-0.049	-0.405	-0.324	-0.301	-0.291	0.068	0.088	0.122	0.085
	(-0.98)	(-0.82)	(-0.56)	(-0.82)	(-1.55)	(-0.72)	(-0.68)	(-0.38)	(-3.09)	(-2.28)	(-2.04)	(-2.16)	(0.50)	(0.65)	(0.94)	(0.52)
High	0.315	0.587	0.596	0.740	0.426	0.681	0.630	0.509	0.349	0.689	0.641	0.325	0.392	0.558	0.588	0.835
	(1.89)	(3.44)	(3.34)	(2.86)	(1.56)	(2.32)	(2.19)	(2.04)	(1.62)	(2.47)	(2.49)	(1.37)	(2.04)	(2.96)	(3.10)	(4.14)
High-Low	**0.449**	**0.701**	**0.674**	**0.861**	**0.622**	**0.770**	**0.709**	**0.558**	**0.754**	**1.013**	**0.942**	**0.616**	**0.324**	**0.470**	**0.455**	**0.749**
	(2.18)	**(3.57)**	**(3.49)**	**(2.87)**	**(2.33)**	**(2.73)**	**(2.57)**	**(2.00)**	**(3.36)**	**(4.09)**	**(4.09)**	**(2.42)**	**(1.58)**	**(2.65)**	**(2.41)**	**(2.78)**

	Economic condition								Sentiment							
	Non-crisis				Crisis				Low				High			
Portfolios	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}	α_{FF5}	α_q	α_{BS6}	α_{DHS3}
Low	-0.177	-0.169	-0.146	-0.194	-0.078	-0.015	-0.044	0.020	-0.466	-0.529	-0.463	-0.384	-0.081	-0.007	-0.002	-0.004
	(-2.04)	(-1.90)	(-1.57)	(-2.06)	(-0.52)	(-0.11)	(-0.31)	(0.13)	(-3.86)	(-4.61)	(-3.48)	(-2.31)	(-0.77)	(-0.07)	(-0.02)	(-0.04)
High	0.300	0.515	0.546	0.308	0.596	0.840	0.774	1.144	0.289	0.268	0.347	0.406	0.387	0.694	0.670	0.670
	(1.59)	(2.76)	(2.70)	(1.70)	(3.02)	(3.17)	(3.18)	(3.64)	(1.11)	(1.22)	(1.22)	(1.30)	(2.07)	(3.42)	(3.53)	(2.98)
High-Low	**0.477**	**0.684**	**0.692**	**0.502**	**0.674**	**0.854**	**0.818**	**1.124**	**0.755**	**0.797**	**0.809**	**0.790**	**0.469**	**0.701**	**0.672**	**0.674**
	(2.42)	**(3.50)**	**(3.21)**	**(2.33)**	**(2.38)**	**(2.71)**	**(2.74)**	**(2.88)**	**(1.99)**	**(2.25)**	**(2.27)**	**(1.83)**	**(2.28)**	**(3.23)**	**(3.29)**	**(3.02)**

Appendix A

Table A1: Summary statistics: Newspaper dataset

The table reports on the availability and total number of articles collected from each newspaper. All newspaper articles except for the Wall Street Journal are from Nexis. The articles are collected using the power search function and a "relevance score" of 80% or more. Wall Street Journal articles come from ProQuest and in the search function, we jointly use keywords such as 'Stock Index', 'S&P 500', and 'Stock Market', and we require these to be present in the abstract, heading, and main text. Availability is the maximum of the start of the sample period. The sample period is from January 1990 to September 2022.

# Newspapers	Availability	Articles	Percentage of total
(1) Atlanta Journal and Constitution	1991-2022	2,551	3.88%
(2) The Augusta Chronicle	1993-2018	2,018	3.07%
(3) The Austin American-Statesman	1995-2022	1,358	2.06%
(4) Daily News (New York)	1995-2022	839	1.27%
(5) Dayton Daily News	1994-2018	1,754	2.66%
(6) The New York Post	1997-2022	2,913	4.43%
(7) The New York Times	1990-2022	11,175	16.98%
(8) The Palm Beach Post	2011-2018	150	0.23%
(9) The Philadelphia Inquirer	1994-2022	2,962	4.50%
(10) Pittsburgh Post-Gazette	1990-2022	5,470	8.31%
(11) Richmond Times Dispatch	1996-2018	377	0.57%
(12) S&P Daily News	1990-2018	1,629	2.47%
(13) The Salt Lake Tribune	1995-2020	1,151	1.75%
(14) The Santa Fe New Mexican	1995-2022	88	0.13%
(15) St. Louis Post Dispatch	1990-2022	4,222	6.41%
(16) Star Tribune (Minneapolis)	1991-2022	718	1.09%
(17) Tulsa World	1995-2018	4,312	6.55%
(18) The USA Today	1990-2022	7,356	11.18%
(19) Wall Street Journal	1990-2022	6,987	10.61%
(20) The Washington Post	1990-2022	7,424	11.28%
(21) Wisconsin State Journal	1995-2022	371	0.56%
Total articles		65,825	100.00%
Total of NYT, WP, USAT, WSJ		32,942	50.04%

Table A2: Correlations among integral and incidental emotion betas

The table presents correlation between emotion, mood, sentiment, uncertainty, and tone betas. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and a set of factors listed in equation (2). Then, we take the absolute value of β^{MEI}. The mood beta (β^{Mood}) of Hirshleifer et al. (2020) is computed by running a 5-year rolling regression of excess stock returns on equal-weighted CRSP excess returns during prespecified and realized high and low mood months. Prespecified high mood months are January and March, and low mood months are September and October. The realized extreme positive and negative mood periods are identified using the top and bottom two months ranked based on the equal-weighted CRSP excess returns realized in a given year. The sentiment beta (β^{SENT}) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index and a set of factors listed in equation (2). We generate the consumer confidence beta (β^{UMCCI}) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and a set of factors listed in equation (2). Following Bali et al. (2017), we compute the uncertainty beta (β^{UNC}) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta (β^{EPU}) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and a set of factors listed in equation (2). We derive two tone betas (β^{LM} and β^{HN}) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and a set of factors listed in equation (2). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries respectively. The estimation period is from January 1995 to September 2022.

Panel A: Correlation between absolute emotion beta and incidental betas							
	β^{Mood}	β^{SENT}	β^{UMCCI}	β^{UNC}	β^{EPU}	β^{LM}	β^{HN}
β^{MEI}	0.255	-0.026	0.000	0.084	0.083	-0.027	-0.024
Panel B: Correlation between directional emotion beta and incidental betas							
	β^{Mood}	β^{SENT}	β^{UMCCI}	β^{UNC}	β^{EPU}	β^{LM}	β^{HN}
β^{MEI*}	-0.006	-0.071	-0.147	-0.124	0.129	-0.082	-0.119

Table A3: Fama-MacBeth cross-sectional regression estimates using valence-based emotion beta

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion beta (β^{MEI}), valence-based MEI emotion beta ($\beta^{Valence}$) and a set of lagged control variables using the Fama-MacBeth method. We compute valence-based MEI as the ratio of difference between excitement and anxiety word counts to total words in a month. We then estimate valence-based emotion beta (β^{MEI}) by estimating a 60-month rolling regressions of excess stock returns on valence-based MEI and a set of factors listed in equation (2). The control variables are market beta (β^{MKT}), volatility beta (β^{VIX}), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported below the estimates. The estimation period is from January 1995 to September 2022.

	Without industry effects				With industry effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{MEI}	0.253	0.251	0.229	0.094	0.211	0.209	0.197	0.090
	(3.47)	(3.70)	(3.83)	(2.12)	(3.66)	(3.87)	(4.07)	(2.34)
$\beta^{Valence}$	0.045	0.036	0.020	-0.018	0.046	0.036	0.021	-0.005
	(0.78)	(0.63)	(0.33)	(-0.36)	(0.96)	(0.73)	(0.43)	(-0.12)
β^{MKT}		0.063	0.051	0.050		0.041	0.037	0.048
		(0.98)	(0.82)	(0.92)		(0.75)	(0.70)	(1.00)
β^{VIX}		-0.274	-0.310	-0.114		-0.229	-0.276	-0.105
		(-1.60)	(-1.90)	(-2.85)		(-1.58)	(-1.93)	(-2.94)
SIZE			-0.205	-0.115			-0.210	-0.118
			(-3.05)	(-2.00)			(-3.09)	(-2.10)
B/M			-0.314	-0.389			-0.261	-0.364
			(-3.68)	(-4.78)			(-3.47)	(-4.92)
MOM			-0.134	-0.322			-0.145	-0.328
			(-0.95)	(-2.25)			(-1.17)	(-2.51)
REV				-0.230				-0.241
				(-3.90)				(-4.33)
I/A				0.441				0.421
				(10.15)				(10.59)
ROE				0.934				0.888
				(4.00)				(4.06)
ILLIQ				0.793				0.774
				(2.38)				(2.70)
IVOL				0.782				0.800
				(8.75)				(9.72)
MAX				-0.677				-0.723
				(-5.99)				(-7.20)
Intercept	1.324	1.323	1.249	1.070	0.986	1.475	1.229	0.928
	(4.52)	(4.55)	(4.29)	(3.86)	(2.57)	(3.69)	(3.00)	(2.69)
Adj. R-squared	0.92%	2.15%	3.87%	6.27%	5.36%	6.22%	7.55%	9.54%
N months	333	333	333	333	333	333	333	333

Table A4: Ten most frequent emotional and tonal words

The table presents 10 most frequent emotional and tonal words. We compute excitement and anxiety word counts using Taffler et al.'s (2023) 'excitement' and 'anxiety' keyword dictionaries. positive and negative word counts are based on Loughran and McDonald (2011) positive and negative dictionaries. The words are counted using articles from 21 newspapers (see Table A1 for the list of newspapers) from January 1990 to September 2022.

Word	Excitement	Anxiety	Positive	Negative
1	Rise	Fall	Gain	Decline
2	Jump	Worry	Good	Loss
3	Climb	Risk	Strong	Cut
4	Confident	Fear	Better	Lost
5	Boost	Bear Market	Best	Concern
6	Bull Market	Volatile	Confident	Fear
7	Surprise	Tumble	Boost	Slow
8	Speculate	Pressure	Improve	Severe
9	Optimism	Uncertainty	Benefit	Volatile
10	Expand	Struggle	Rebound	Bad

Table A5: Proportion of articles across MEI and tone scores

The table reports the percentages of articles across quintiles of market emotion index and tone over the sample period. The market emotion index is the total of excitement and anxiety word counts to the total words in a month. We compute excitement and anxiety word counts using Taffler et al.'s (2023) 'excitement' and 'anxiety' keyword dictionaries. Tone is the ratio of difference between positive and negative word counts to the total of positive and negative word counts based on Loughran and McDonald (2011) positive and negative dictionaries. The sample period is from January 1990 to September 2022.

			Market Emotion Index				
	Quintile		1	2	3	4	5
		Scores	0.013	0.028	0.039	0.052	0.078
Tone	1	-0.861	**0.064**	0.041	0.035	0.032	0.031
	2	-0.573	0.034	**0.040**	0.042	0.040	0.041
	3	-0.354	0.030	0.040	**0.043**	0.042	0.045
	4	-0.106	0.038	0.041	0.044	**0.046**	0.047
	5	0.278	0.033	0.037	0.037	0.039	**0.036**

Appendix B

Case Study 1

The New York Times
November 29, 2009 Sunday
Late Edition – Final

A Rally That Needs More 'E'

In the first leg of a bull market, when optimism and euphoria are ascendant, investors are willing to bet that the economy will improve and that corporate profit growth is just around the corner. This faith manifests itself not just in rising share prices, but also in rising price-to-earnings ratios.

True to form, the P/E ratio for companies in the Standard & Poor's 500-stock index has soared 87 percent since this rally began on March 9.

But hope can take the market only so far. Earnings -- the "E" in the P/E ratio -- must soon recover and become the catalyst for rising prices if this rally is to last. All reports so far, however, show that earnings are still falling.

"The early-cycle P/E expansion is most likely behind us," said Jeffrey N. Kleintop, chief market strategist at LPL Financial in Boston. From here on, he said, corporate profits will have to be strong enough to propel stock prices higher.

What makes him think so? For starters, P/E expansion alone has already lifted the market by more than 60 percent since early March, in one of the strongest short-term surges in recent memory.

But long-term history also offers an important clue.

Though conventional wisdom assumes that P/E ratios continue to grow throughout a bull market, that's not always the case. In fact, it's rarely the case.

On average, the market's P/E tends to peak a little more than a year into a bull market, according to analysis by Ned Davis Research, an investment consulting firm in Venice, Fla. "And the lion's share of that P/E expansion takes place in the first six months," said Ed Clissold, senior global analyst at Ned Davis.

Indeed, Ned Davis researchers found that price-to-earnings ratios shot up 28 percent, on average, in the first 15 months of bull markets since 1929. But four-fifths of that expansion took place within the first six months.

Sam Stovall, chief investment strategist at S.& P., analyzed bull markets back to 1942 and found that in 9 of the last 11, the S.& P. 500's P/E ratio grew within the first year by an average of 29 percent.

In the second year of those run-ups, though, the market's P/E ratio actually fell -- by 6 percent, on average. What's more, in bull markets that survived into a third year, the P/E continued to slip.

In many cases, that's because corporate profits expand so fast that their growth outpaces rising share prices. In other words, as the "E" in the P/E ratio grows faster than the "P," the multiple contracts even as stocks gain ground.

As for the current decline in corporate profits, the best that can be said is that the rate of contraction has slowed. At the start of October, Wall Street analysts were bracing for a 24.8 percent decline in S.& P. 500 profits in the third quarter, versus the same period a year ago. Today, the consensus estimate is for a much more modest fall, of 13.7 percent.

When will the earnings outlook turn around?

For a while now, analysts have been predicting that corporate profits will start growing in 2010. And, recently, some market strategists have begun raising their forecasts for next year. David Bianco, chief domestic equity strategist at Bank of America Merrill Lynch, for example, lifted his target for S.& P. 500 earnings to $73 a share in 2010, from $70.

Mr. Kleintop of LPL says his target for S.& P. profits stands at around $75 a share for next year, but adds that he would not be surprised if it ended up closer to $77 a share.

Still, he says he believes the S.& P. 500 will end 2010 at around 1,200. That would be up 10 percent from the current level and a 7 percent climb from 1,125, which is where Mr. Kleintop thinks the index will end this year.

Even if this rally survives through 2010 -- and that's a big if – modest returns may be all that can be expected.

After all, as investors shift their attention to the fundamentals, the euphoria is likely to die down.

Score: MEI 0.04 and LM 0.00

Case Study 2

Wall Street Journal
January 13, 2004 Tuesday
Eastern edition; New York, N.Y.

Stocks Resume Rally After a 1-Day Break; Earnings Data Loom

After seven weeks of market gains, stocks began the new week with yet another advance amid optimism about coming fourth-quarter earnings reports.

The Nasdaq Composite Index, whose many technology stocks slumped in mid-December, surged to another 30-month high, rising 1.19%, or 24.86 points, to 2111.78. The Dow Jones Industrial Average rose 26.29 points, or 0.25%, to 10485.18, short of the 21-month high of 10592.44 hit Thursday.

Optimism about earnings overshadowed last week's worries about the weak December employment report, which knocked stocks down on Friday. Bellwether Intel will release quarterly earnings tomorrow and General Electric will on Friday.

Stocks began yesterday with a slump, as several analysts warned that the market is overdue for a pullback. But by day's end, stocks were headed up again.

"It appears that the flow of dollars into stock mutual funds continues to be strong, and investors are encouraged about the rebound in the economy" and in earnings, said Tim Heekin, director of trading at San Francisco brokerage firm Thomas Weisel Partners.

The dollar rebounded as comments from European Central Bank President Jean-Claude Trichet were taken as a hint that the ECB might intervene to keep the euro from rising too high against the dollar. Gold fell slightly, as did Treasury bonds. One cloud was the continued rise in the price of oil, to $34.72, the highest finish since March of last year.

The broad S&P 500 index rose 0.48%, or 5.37 points, to 1127.23, just short of the 21-month high it hit last week.

In major U.S. market action:

Stocks advanced. On the Big Board, where 1.46 billion shares traded, 2,063 stocks rose and 1,220 fell.

Bonds declined. The 10-year Treasury note fell 2/32, or 62.5 cents for each $1,000 invested. The yield, which moves inversely to price, rose to 4.087%. The 30-year bond was down 9/32 to yield 4.979%.

The dollar strengthened. It traded at 106.69 yen, up from 106.37 yen, while the euro fell against the dollar to $1.2747 from $1.2843.

Score: MEI 0.02 and LM 0.00

Appendix C

Emotion Dictionary

Taffler et al. (2023) build their emotion keyword dictionary by analyzing U.S. media reports from a range of sources during the Internet bubble as a wide range investor emotions manifest during this period. Keyword-in-context (KWIC) was employed to ensure all emotions words used had direct market relevant emotional content. The initial stage in their dictionary development was an analysis of media reports published in widely-circulated U.S. newspapers from October 1998 to September 2002. The resulting emotion word list was then supplemented using Harvard IV-4 GI and Lasswell Value dictionaries, and further enriched by important human emotion words from the *Book of Human Emotions* (Watt-Smith, 2015). Additional details about the dictionary construction process are available in Taffler et al. (2023).

Keywords used to define the emotion dictionary	
Excitement:	Appetite, Appetiser, Appetising, Appetizer, Appetizing, Awesome, Awesomeness, Boost, Boosted, Booster, Boosting, Boosts, Brilliance, Brilliant, Brilliantly, Bull Market, Celebrate, Celebrated, Celebrating, Celebration, Celebrity, Climb, Climbed, Climber, Climbing, Climbs, Confidence, Confident, Confidently, Curiosity, Curious, Delight, Delighted, Delightful, Desirability, Desirable, Desire, Desired, Desires, Desiring, Double, Doubled, Doubles, Doubling, Eager, Eagerly, Eagerness, Enthuse, Enthusiasm, Enthusiast, Enthusiastic, Enthusiastically, Excite, Excited, Excitement, Excites, Expand, Expanded, Expanding, Expands, Expansion, Fantastic, Fantastically, Ferocious, Ferociously, Flourish, Flourished, Flourishes, Flourishing, Glorious, Glory, Happiness, Happy, Jump, Jumped, Jumping, Jumps, New High, Optimism, Optimist, Optimistic, Optimistically, Popular, Popularity, Popularize, Popularly, Pride, Proud, Ramp Up, Reliability, Reliable, Rise, Risen, Rises, Run Up, Run-Up, Satisfaction, Satisfied, Satisfy, Sensation, Sensational, Sensationally, Sexy, Shoot, Shooter, Shooting, Shoots, Shot, Speculate, Speculated, Speculates, Speculating, Speculation, Speculations, Steal, Stealing, Steals, Stole, Stolen, Success, Successful, Successfully, Superior, Superiority, Surprise, Surprised, Surprises, Surprising, Surprisingly, Triple, Tripled, Triplet, Unprecedented, Winner.
Anxiety:	Afraid, Anxiety, Anxious, Anxiously, Anxiousness, Avoid, Avoidance, Avoided, Avoiding, Avoids, Bear Market, Calm, Calming, Caution, Cautionary, Cautioned, Cautioning, Cautions, Cautious, Confuse, Confused, Confuses, Confusing, Confusingly, Confusion, Cool, Cooled, Cooler, Cooling, Cooling Off, Cooling-Off, Cools, Cools Off, Danger, Dangerous, Dangerously, Dead, Deadly, Death, Deathly, Die, Dies, Dying, Depress, Depressed, Depressing, Depression, Difficult, Difficulties, Difficultly, Distress, Distressed, Distressing, Excess, Excesses, Excessive, Excessively, Fall, Fallen, Falls, Fear, Feared, Fearful, Fearing, Fears, Fearsome, Falter, Faltered, Faltering, Falters, Flameout, Flame-Out, Frighten, Frightened, Frighteningly, Frightens, Hazard, Hazardous, Jitter, Jitters, Jittery, Liable, Nerve, Nerves, Nerviness, Nervous, Nervously, Nervousness, Nervy, Overheated, Overhyped, Over-Hyped, Pessimism, Pessimist, Pessimistic, Pessimistically, Pressure, Pressured, Pressures, Pressuring, Reluctance, Reluctant, Risk, Risked, Riskier, Riskiness, Risks, Risky, Scare, Scared, Scares, Scaring, Scary, Shake Out, Shakeout, Shake-Out, Shrink, Shrinkage, Shrinking, Shrinks, Shrunken, Stress, Stressed, Stresses, Stressful, Stressing, Struggle, Struggled, Struggles, Struggling, Threat, Threaten, Threatened, Threatening, Threatens, Tumble, Tumbled, Tumbles, Tumbling, Uncertain, Uncertainly, Uncertainty Uncomfortable, Uncomfortably, Unease, Uneasily, Uneasiness, Uneasy, Unreliability, Unreliable, Volatile, Volatility, Vulnerability, Vulnerable, Wonderful, Wonderfully, Wondrous, Worried, Worries, Worry, Worrying.