Investor emotions and the cross-section of stock returns

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Abstract

Stock market participation meets investors' emotional needs as well as their financial ones. We propose that investors enter into emotional relationships with stocks they invest in and show that it is possible to measure variation in individual stock sensitivity to investors' emotional demands. Specifically, we find our firm-specific emotion betas which measure stock emotional utility to investors are priced in the cross-section. A long-short investment strategy of buying high-emotion beta stocks and selling low-emotion beta stocks generates significant alpha. This factor premium derives, in particular, from the outperformance of high-emotionally-charged beta stocks. Investors obtain a greater emotional utility from small growth stocks in contrast to large value stocks. Our findings demonstrate empirically the important role investor emotions play in the pricing of stocks.

Keywords: Asset pricing, Market emotion index, Emotional utility, Return predictability, Object relations theory

JEL classification: G12, G14, C13

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"Emotions constitute potent, pervasive, and predictable drivers of decision making… [and] are for better or worse, the dominant driver of most meaningful decisions in life." (Lerner et al., 2015)

1. Introduction

The role emotions play in decision-making is an increasing focus of psychological science.[2] However, although financial economists recognize the role of 'incidental' emotions such as weather, sentiment, and mood (e.g., Hirshleifer and Shumway, 2003; Edmans, Garcia, and Norli, 2007; Hirshleifer, Jiang, and DiGiovanni, 2020) in investment decisions, the part played by 'integral' emotions, excitement, anxiety, fear, panic, anger, guilt etc., is largely missing from the finance literature (e.g., Summers and Duxbury, 2012). In this paper, we measure the emotional relationships investors enter into with the stocks they invest in, and the asset-pricing implications.

The motivation for our study comes from the emotions in decision-making literature (e.g., Lerner et al., 2015), and object relations theory in psychology. This latter describes the ambivalent relations of attachment, attraction and repulsion ('love' and 'hate'), we establish in our minds with 'objects', the internalized 'representations' of people, ideas, or things based on our experiences of early emotional relationships (e.g., Tuckett and Taffler, 2012, pp. 84-86; Auchincloss and Samberg, 2012, pp. 175-178). These are often beyond our conscious awareness and are even more powerful as a result. We conjecture investors enter into emotional relationships with stocks which affect their perceptions of risk and return.[3] We estimate stocks' emotional utility (EU) for investors, and demonstrate how this can predict cross-sectional variation in future stock returns.

The rational economic investor notionally maximizes utility, possesses unlimited information processing capability and shows predictable and stable preferences. However, real world investors deviate from such a rational-choice model not fit into this idealized model, and are driven by a myriad of different influences. Even sophisticated investors are prone to emotional conflict as many of the investment decisions they make are predominantly emotional in nature (Kuhnen and Knutson, 2011; Tuckett and Taffler, 2012).

[2] In this paper, following the psychological literature we use the terms 'emotion', 'affect', and 'feeling' interchangeably to convey subjective experience (Auchincloss and Samberg, 2012, pp. 8-10).

[3] In-depth interviews with fund managers in fact suggest many of their investment decisions are largely emotional in nature even if they do not acknowledge this directly (Taffler, Spence, and Eshraghi, 2017).

Our endeavor is important in several ways. First, we link the emotional utility stocks have for investors with cross-sectional return predictability. We find that it is the emotional intensity of investor engagement with a stock that is priced rather than simply its valence (positive/negative) consistent with the affective circumplex model of emotions.[4] (e.g., Posner, Russell, and Peterson, 2005; Posner et al., 2009). As e.g., Lerner and Keltner (2000) and DeSteno et al. (2000) point out, different emotions of the same valence influence judgments and choices in dissimilar ways. For example, Lerner and Keltner (2001) document that fearful individuals make pessimistic judgements whereas angry individuals make optimistic judgements even though fear and anger have the same negative valence. 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.

Second, the integral emotions we focus on differ from incidental emotions which are less context specific and can be attenuated by revealing what is driving them (Schwarz and Clore, 1983). Integral emotions, on the contrary, are fundamental and often unconscious, and at sufficient levels of intensity can bewilder cognitive processing (Loewenstein and Lerner, 2003). Specifically, we find empirically that a wide range of powerful investor emotions collapse into two meta-emotional states we broadly label as 'excitement' and 'anxiety' and which reflect the underlying neuroscience of emotional brain processes (Kuhnen and Knutson, 2011). These emotions modify investors' risk perceptions, or beliefs, or both. Drawing on object relations theory and the emotions in decision-making literature, we measure the time varying emotional utility individual stocks have for investors in terms of the feelings of excitement and anxiety they generate.

In the face of stock market unpredictability, the pleasure of imagined future gains in the minds of investors can be thought of as creating feelings of excitement, and the pain of potential loss that of anxiety. This continuing struggle between excitement and anxiety means investment activity generates ambivalent object relations, and thus is inevitably highly emotionally charged. These assertions provide strong a priori motivation to use measures of emotional utility in seeking to predict stock returns.

[4] 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. The combination of these two determines how individuals experience and refine emotional states.

Third, since much of the information investors use to make stock selection decisions is provided by the media, news articles can be used to reflect the emotional resonances of individual stocks for investors. As 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 the media content mirrors feelings about the state of the stock market dynamically (see, for example, Tetlock, 2007; Dougal et al., 2012; Shiller, 2019), we employ news articles to measure salient contemporaneous investor emotions, and use these to construct our market emotion index which allows us to generate the investor emotional utility measures we employ in our empirical analysis. Specifically, we quantify investor emotion utilizing national- and local-level newspaper articles relating to the stock market.

Our main contribution is to quantify the emotional attraction individual stocks have for investors, and how this can be used to predict the cross-section of stock returns. The emotional meaning stocks have for investors has attractive properties for understanding their decision processes. First, as Loewenstein (2000) points out, feelings often direct behavior in different directions to those prescribed by costs and benefits. As such investor emotions, both conscious and unconscious, can influence their equity valuations and investment judgements. Second, our findings confirm those of experimental stock markets which demonstrate how emotions are closely related with investment decisions (e.g., Andrade, Odean, and Lin, 2016; Breaban and Noussair, 2018). Third, the stock market environment is one where feelings of excitement and anxiety and related emotions are likely to dominate due to the inherent unpredictability of future returns (Taffler, Spence, and Eshraghi, 2017).

To measure investors' emotional utility, we adopt a standard bag-of-words technique with keyword dictionaries made up of 134 excitement-related words and 161 anxiety-related words. These lexicons were originally constructed to analyze the emotional morphology of the highly-charged internet asset-pricing bubble by systematically analyzing contemporaneous media coverage using a keyword-in-context (KWIC) approach and also manifest out-of-sample validity (Taffler, Agarwal, and Obring, 2021).[5] For each month in our sample period January 1990-December 2018 we use the ratio of difference between excitement and anxiety word

[5] Specifically, these lexicons were found to work equally well in exploring the emotional dynamics of the U.S. stock market during the Global Financial Crisis. Our empirical analysis is also providing an implicit test that the measures of investor emotional state we use are robust over time and in non-crisis periods.

counts in the newspaper articles we analyze to the total of excitement and anxiety words to derive our market emotion index which measures investor emotional engagement with the stock market.

To explore how stock emotional utility might influence prices, we estimate stock emotion betas using a rolling regression based on our market emotion index to capture cross-sectional variation in emotional charge for investors across stocks. We hypothesize that investors are more (less) attracted to stocks with high (low) emotion beta, and this affects their pricing. Consistent with affective circumplex model, it is the strength of the emotional charge (beta), which measures stock emotional utility to investors is priced. The more powerful the emotional charge or investor 'arousal', the greater the propensity to invest. Conversely, the weaker the emotional utility, the lower the appeal the stock has.

We estimate individual firm emotion betas to measure the return sensitivity of individual stocks to investor emotions by employing a time-series rolling regression of individual stock returns on the market emotion index. Specifically, we employ 60-month rolling regressions of excess returns on the index for each stock trading on the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq. The monthly emotion betas generated are then transformed into conditional emotion-sensitive betas by taking their absolute values as investors are, in line with object relations theory and the circumflex model of affect, driven by the intensity of the emotional charge rather than its valency. We then examine the ability of these stock emotion betas to predict cross-sectional variation in expected returns.

To do this, we sort stocks into quintile portfolios based on previous month conditional emotion beta, and measure the monthly returns of the resulting portfolios. Between January 1995 and December 2018, the high-minus-low portfolio earns an abnormal return of 0.41% per month after controlling for the Fama-French five factors with *t*-statistic of 5.23, and a characteristic-adjusted average excess return of 0.54% per month with a *t*-statistic of 3.80. Our emotion beta-based high-minus-low trading strategy generates qualitatively similar alpha when we consider time-varying systematic (economy-wide) risk factors. Reflecting the fundamental nature of integral emotions in decision-making processes, we find emotion beta stock sensitivity persists for up to 60 months. Likewise, we show an emotion beta-based trading strategy generates economically significant alpha for up to four months, again demonstrating the power of emotions in driving investor behavior. We conclude that investor emotions can predict the cross-section of stock returns. Stocks with high emotion beta earn higher returns than low beta ones. In parallel, the emotion beta in a monthly Fama and MacBeth (1973) regression has a coefficient of 0.55 with t-statistic of 4.06. In economic terms, this implies at one standard deviation shift in conditional emotion beta is associated with a 1.35% [= 0.55 × 2.45] shift in stock return in the following month. We find that the predictive ability of emotion beta remains strong up to eight months ahead in a Fama-MacBeth framework.

We examine the robustness of our findings by performing additional tests. First, we measure emotion beta with alternative specifications and variations in factor models, and show that it remains a significant predictor of future stock returns. In each case, by following a high-minus-low trading strategy, investors can earn positive and significant abnormal return. Second, we explore whether our integral emotion beta predictability is distinct from that of incidental emotions such as seasonal mood (e.g., Hirsleifer et al., 2020), valence such as sentiment (Baker and Wurgler, 2006), positivity-/negativity-based textual tone (Loughran and MacDonald, 2011; Henry, 2008), and both Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and Bali, Brown, and Tang's (2017) economic uncertainty index betas. We find in all cases our emotion beta still generates a positive and significant coefficient in a Fama-MacBeth framework. This indicates the unique contribution of emotion beta in predicting future stock returns. Third, following Ball et al. (2020) we control for microcaps and results are unchanged. Fourth, our hedge portfolio produces significant alphas when we consider S&P 500 stocks, the largest 1000 stocks, and the 1000 most liquid stocks separately. Fifth, we construct several variants of the market emotion index and find similar results. Sixth, our results are qualitatively similar across a range of emotion beta-based extreme portfolios.

Overall, our findings confirm empirically how stock market investing is a highly emotionally-charged process reflecting the emotional relationships investors enter into with their stocks, which are mirrored in their investment decisions. The emotional utility different stocks have for investors is priced in the cross-section. The intensity of investor emotional stock object relations adds to conventional fundamental asset valuation criteria. Investors' expectations of future gain, both as individuals and as a group, create excitement, but with the associated anxiety of future loss. Such an uncertainty-driven emotional process is ongoing, and as our results suggest, is an important driver of stock pricing.

We contribute to the asset pricing literature by introducing the pricing implications of investor feelings of excitement and anxiety. Our novel emotion beta measure shows that such emotions can generate mispricing in the stock market. Our key innovation is to recognize the heterogeneity in the investors' integral emotion levels. To the best of our knowledge, this is the first study to show the direct impact of investor integral emotions in the cross-section of stock returns in real-world markets. Our findings contribute to the growing literature that examines the relationship between such incidental emotions such as mood, sentiment, and weather by introducing the parallel impact of integral emotions on investor decision making.

Beyond the literature on mood and asset pricing, our paper also extends the return predictability literature (e.g., Cohen and Frazzini, 2008; Lou, 2014; Addoum and Kumar, 2016; Lee et al., 2019). In particular, our paper identifies a new return predictability mechanism and provides associated empirical evidence. More generally, our results lend support to behavioral asset pricing models that show investor sentiment takes stock prices away from fundamentals and arbitrageurs eventually correct this mispricing (De Long et al., 1990; Baker and Wurgler 2006). Further, our results supplement the news and finance literature by showing how news is incorporated in market pricing through the investor emotions it generates (Shiller, 2019). Finally, our study contributes to the investment psychology and decision-making literatures showing how often nonconscious fundamental emotions can drive investor behavior.

The rest of the paper is organized as follows. Section 2 provides a brief background on emotions and decision making. We also develop our testable hypotheses. Section 3 describes data and methodology. Section 4 discusses empirical results and section 5 concludes.

2. Background and hypotheses

Our emotion-driven return predictability hypothesis is motivated by the psychology of integral emotions and research into the relationship between mood and sentiment, and stock returns. For example, at the aggregate stock market level, seasonal affective disorder (SAD) induced depression and sunlight-influenced mood affect stock returns (e.g., Kamstra, Kramer, and Levi, 2003; Hirshleifer and Shumway, 2003). In parallel, cross-sectionally, Hirshleifer et al. (2020) also find seasonal variation in mood can explain stock return seasonality. In particular, they find stocks with greater sensitivities to aggregate mood earn higher returns during high mood periods and lower returns during low mood periods. Similarly, the previous literature has also shown that investor sentiment can explain and predicts stock returns although investor sentiment itself is difficult to measure (Baker and Wurgler (2006). Likewise, Edmans et al. (2007) link soccer outcome-driven changes in investor sentiment with aggregate stock market return in the short-term. Edmans et al. (2020) demonstrate that music sentiment impacts market returns and volatility consistent with sentiment induced temporary mispricing.

Taken together, these studies indicate mood and sentiment can influence market valuation and stock returns. However, they focus on feelings that are not directly linked to investment decision making – incidental emotions. Incidental emotions are less decision context specific (Watson and Tellegen, 1985) and tend to be very short-lived. In contrast, motivated by research in the psychology of emotions, we contribute by exploring how the integral or fundamental emotions investors experience at the time of financial decision-making affect asset prices in a predictable manner.

Integral emotions, as the emotion-imbued choice model of Lerner et al. (2015) illustrates, enter directly or indirectly into the investor choice process that both consciously and nonconsciously affects decision-making, and which is outside the scope of rational choice models. The effects of integral emotions are very difficult to avoid (Rozin et al., 1986) and are remarkably influential even in the presence of cognitive information (Loewenstein, 1996). The intensity of such fundamental emotions progressively takes over and overrides rational courses of action (Loewenstein, 1996; Loewenstein et al., 2001) leading to investors becoming bounded rational, and through their emotions making satisfying rather than optimal decisions (see Kaufman, 1999; and Hanoch, 2002).

We introduce the concept of emotional utility, i.e., investors' need to enter into an emotionally-charged relationship with the stocks they invest in that has pricing implications. We conjecture that investors experience different emotions about the stocks they invest in such as those of excitement and anxiety, which we parsimoniously work with in this paper, and enter into ambivalent object-relationships with these stocks which affect their stock preferences. Barber and Odean (2008) show that investors create a set of attractive stocks that grab their attention before making the final investment decision. In the same way, we argue that investors are attracted to, value, and invest in stocks having emotional 'glitter', i.e., high emotional utility, which leads to price pressure in the market for these stocks.

We propose that investors enter into ambivalent object-relationships with stocks of a love and hate nature. A stock's emotion beta captures the strength of this object-relationship. Once such an emotional bond exists, investors derive emotional utility from their investment that is reflected in the cross-section of stock returns. The magnitude of a stock's emotion beta is associated with its demand and supply. Thus, we expect emotion beta to generate mispricing in the cross-section and predict future stock returns. Importantly, consistent with affective circumflex model of neurophysiological emotional processes which distinguishes the processing of valence and arousal. We work specifically with the level of arousal i.e., strengths of emotional attraction the stock has for investors. This leads us to our first testable hypothesis:

Hypothesis 1: (The emotion beta effect): Emotion beta, which measures an asset's return sensitivity to the market emotion index, positively predicts the cross-section of security returns.

We speculate that trend chasers and contrarians will both covet high emotion beta stocks as they expect to derive higher emotional utility from them. Trend chasers will buy more in up market whereas contrarians will be invest more in down market. In both cases, investor demand will drive the price up at least in the short-term because, as Barber an Odean (2008) suggest investors focus only on future returns when making investor decisions. Furthermore, we would expect emotion beta to be higher for stocks whose valuations are more subjective and vary to a greater extent with respect to speculative demand such as small and growth stocks. Conversely, large value stocks are likely to have low emotion utility and thus be less attractive for investors. Our second hypothesis follows:

Hypothesis 2: The stock returns of high emotion beta portfolios will outperform low emotion beta portfolio returns.

Study of the impact of powerful emotions such as excitement and anxiety on investor judgments has been limited to date in the finance literature compared to research on nonstandard investor preferences such as prospect theory, and incidental emotions such as weather, mood, and sentiment. Overall, we add to the research evidence on how emotion affects investment decision-making by considering the emotional representation of stocks in the minds of investors and the associated asset-pricing implications.

3. Data and variable definitions

This section describes how we measure emotion beta, our stock-level predictor variables, assess cross-section stock return predictability and the data sets we draw on. Analysis covers the period from January 1990 to December 2018.

3.1 Measuring and quantifying emotion

It is challenging to measure and quantify emotion. The media helps generate, and also reflects its readers emotions (Shiller, 2019). As such, newspaper articles are an ideal source to measure investor emotions about the stock market. However, newspapers do not 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 thus poses a barrier to constructing an appropriate dataset at the individual firm level directly. Consequently, we collect news items about the S&P 500 index, which newspapers cover extensively on a daily basis and use these to construct the market-level emotion index we work with, and employ to generate individual monthly stock betas.

Table A2 reports that we work with 59,665 news articles collected from 21 national and local level newspapers, breaks down the number of articles by newspaper and provides respective period coverage. The four widely-circulated national-level US newspapers – The New York Times, The Washington Post, Wall Street Journal and USA Today – account for about half of our articles about the S&P 500 index. These news articles are drawn from the Nexis and ProQuest 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%, and containing at least 100 words. We exclude newswires, non-business news, and websites. ProQuest, on the other hand, does not provide any formal relevance score instead ranking articles by relevance. To deal with this issue, we ensure all the keywords are present in the abstract, headline and main text. All *Wall Street Journal* articles are downloaded from ProQuest; Nexis covers all the other newspapers we work with. Both databases have good coverage from 1990 onwards which motivates our study period to be from January 1990 to December 2018.

3.3 The market emotion index

Operationalizing and quantifying emotion, i.e., a stock's emotional charge for, or utility to, investors is key. To measure investors' emotions from news articles, 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). This is as powerful as more complex machine-learning approaches in practice (Henry and Leone, 2016). Using the context-specific emotion keyword dictionaries of Taffler et al. (2021), we categorize emotional word mentions in our news articles in different ways. These lexicons were originally constructed to capture the different powerful investor emotions manifest during the highly emotionally-charged dot.com bubble period, and Taffler et al. demonstrate empirically a similar range of emotions were highly salient during the Global Financial Crisis period. Their seven keyword dictionaries measure investor 'Excitement', 'Anxiety', 'Mania', 'Panic', 'Blame', 'Denial', and 'Guilt' and cover 835 words in total.[6] Using these emotion dictionaries, we also are implicitly testing their validity and applicability across our whole sample period, and particularly during normal market conditions. 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. We measure the relative strength of different emotions in any month in terms of the relative frequency of different categories of emotion keywords.

As described in the introduction the most relevant emotions for our purposes with asset pricing implications are excitement and anxiety. In an experimental setting, Breaban and Noussair (2018) examined the relationship between the emotions of excitement and fear/anxiety, and stock market activity, and Andrade et al. (2016) focused on the role of excitement in explaining stock market bubbles. Tuckett, Smith, and Nyman (2014) also use excitement and anxiety to measure relative sentiment shift reflected by financial narratives that influence financial markets. Most relevant to our work with real world markets, Kuhnen and Knutson (2011) draw on neuroscience to explore investor risk taking behavior and argue that the two affective states of excitement and anxiety influence risk preferences in the emotional brain.[7] We posit investors' emotional relationships with the stocks they invest in that have important asset pricing implications.

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[6] 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* (Smith, 2015). Keyword-in-context was employed to ensure all emotions words used had directly market relevant emotional content. All retained emotion words were then classified using a rigorous and systematic process to one of the seven emotion lexicons.

[7] We also perform a principal component analysis (PCA) of the word counts of the seven categories of emotions in Taffler et al. (2021) and find these collapses into two factors. Excitement relates to the first factor, and anxiety mostly explains the second factor. We also measure market emotion index using the factors derived by principal

We generate emotion word counts using the two Taffler et al. (2021) keyword lexicons of excitement and anxiety, and scale these by total words. We follow Henry and Leone (2016) and generate our market emotion index (*MEI*) measure by:

$$MEI_t = \frac{Excitement_t - Anxiety_t}{Excitement_t + Anxiety_t} \quad \dots \quad (1)$$

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. Henry and Leone (2016) provide evidence in favor of equally weighting of each word counted using the standard bag-of-words technique, and show other weighting schemes such as inverse document frequency offer trivial improvement. Application of more complex procedures such as topic modeling would require looking ahead through all articles before any empirical analysis of market prices leading to hindsight bias. Hence, we choose simplicity and transparency over alternatives that are more elaborate.

We do not use the Loughran and McDonald (2011) and Henry (2008) positive/negative word dictionaries for two reasons in our main analysis although we use these in our robustness tests. First, both dictionaries are not designed to measure investor emotions which is the focus of this paper. Second, Loughran and McDonald's lexicons are developed from 10-K reports that are full of accounting/financial jargon which are unlikely to have significant emotional resonance. Similarly, in the case of Henry (2008) her positive/negative tone measure is based on firms in two industries which were profitable, thus words such as 'adverse', 'loss', 'impairment', and 'missing' do not appear in her negative dictionaries quite apart from them not covering emotion-specific words. Importantly, controling for both LM and Henry's (2008) narrative tone in our robustness tests we find investor emotional states have distinct predictive ability over and above such valency-based positivity/negativity measures.

3.4. Estimating emotion beta

For each month of our sample period, we estimate a stock's emotion beta from the monthly rolling regressions of excess stock returns on the market emotion index over a sixty-month fixed window while controlling for the market factors of Fama and French (1992). The first set

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component analysis, i.e., $MEI_{F,t} = \frac{Factor_1 - Factor_2}{Factor_1 + Factor_2}$. We reconfirm our results using the base measure with parallel measure based on factor scores.

of emotion betas are generated using the sample from January 1990 to December 1994. Then, we use these monthly emotion betas to predict the cross-sectional stock returns in the following month. The monthly rolling regression approach is followed until the sample is exhausted in December 2018. Our rolling window estimation method is similar to that of Bali et al. (2017), and Addoum and Kumar (2016), with the dependent variable monthly excess stock return and independent variables the three Fama-French factors and the market emotion index:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI}.MEI_t + \beta_{i,d}^{1}.MKT_t + \beta_{i,t}^{2}.\mathrm{SMB}_t + \beta_{i,t}^{3}HML_t + \varepsilon_{i,t} \quad \dots \quad (2)$$

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, MKT_t, SMB_t, and HML_t are the monthly market emotion index, market (MKT), small-minus-big (SMB) and high-minus-low (HML) factors at time t, respectively.[8]

We, first, test the predictive ability of the emotion beta using standard Fama- MacBeth (1973) regressions. We, then, sort stocks based on their emotion betas, and construct different emotion-driven portfolios. For our empirical analysis, we work with the conditional measure of β^{MEI} given by $\beta^{MEI} = \left|\beta_{i,t}^{MEI}\right|$ on the basis that stocks which have a higher emotional charge or utility for investors irrespective of valence will have higher β^{MEI}.

We focus on the magnitude of the conditional emotion beta for four reasons. First, emotional intensity represents 'arousal' in a circumplex model of affect (Posner et al., 2009) and increases with the vehemence of valence. The arousal defines emotional states individuals experience that we expect to impact investor decision making in a predictable manner. Second, the strength of the investor emotion is more powerful than its valency. At sufficient levels of intensity emotion overwhelms cognitive processing and directs behavior in directions different from those predicted by rational decision-making (Loewenstein and Lerner, 2003). In our case, we expect the price of stocks to diverge from fundamentals depending on emotion sensitivity and generate mispricing at least in the short-term. Third, the nature of the ambivalent object relations investors enters into with the stock market and individual stocks mean they will be experiencing feelings of excitement and anxiety at the same time both consciously and nonconsciously. Investors invest in stocks believing that they will go up irrespective of their emotional states. Fourth, when stock market is bullish, excited participants will act as trend

[8] In robustness tests, we run the same regression to derive emotion beta using different alternative factor models and with results very similar to those reported in our main analysis.

chasers, and drive prices up further. In parallel, when the market is bearish with anxiety dominating, contrarian investors are likely to create price pressure. In both cases, stock price goes up generating mispricing which eventually erodes as investors become more informed. Thus, we argue that the emotional utility investors experience from the stocks they invest in at the time of investment decision-making ultimately influences and drives asset prices.

3.2 Cross-sectional return predictor data

Monthly stock returns are taken from the Centre 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.

Our Fama-French factor, risk-free rate, and industry classification data are from Kenneth French's data library.[9] The Fama-French factor data we use 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. Our liquidity factor (LIQ) is taken from Lubos Pastor's data library.[10]

We compute book-to-market ratio, denoted BM, as book equity scaled by market equity, where market equity is lagged six months to avoid taking unintentional positions in momentum (Novy-Marx, 2013). 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). Variable definitions mostly consistent with Fama and French (1992) are used in computing stockholders' equity if available, otherwise book value of equity is derived as common equity plus carrying value of preferred stock if available, or total assets minus total liabilities. Redemption value of preferred stock is employed if available, otherwise liquidating value if available, or else carrying value.[11]

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

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

[11] We compute shareholders' equity (SEQ) as common equity (CEQ) plus carrying value of preferred stock (PSTX) or total assets (AT) minus total liabilities (LT). Preferred stock is preferred stock redemption value (PSTKR) or liquidating value (PSTKRL) or carrying value (PSTK). Market equity is price (PRC) multiplied by number of shares outstanding (SHROUT).

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.

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

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

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:

$$R_{i,d}^{e} = \alpha_t + \beta_i . R_{m,d} + \gamma_i . SMB_d + \delta_i HML_d + \varepsilon_{i,d} \quad \dots \quad (4)$$

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

$$R_{i,d}^{e} = \alpha_{i,d} + \beta_{i,d}^{MKT} . R_{m,d}^{e} + \beta_{i,d}^{VIX} . \Delta VAR_d^{VIX} + \delta_i HML_d + \varepsilon_{i,d} \quad \dots \quad (5)$$

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 with 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.

4. Empirical findings

In this section, we present different test results to assess the predictive power of stock emotion sensitivity over future stock returns. First, we start with correlation analysis and present the Fama and MacBeth (1973) regression results. Second, we perform univariate portfolio-level analysis. We also examine conditional factor models, persistence of emotion beta, and longevity of the emotion beta-based mispricing. Third, we examine the distinctiveness of our emotion beta and control for mood, sentiment, economic uncertainty, policy uncertainty, and tone in Fama and MacBeth regressions. Fourth, we conduct bivariate portfolio-level analyses and assess the predictability of the emotion beta after controlling for stock characteristics and risk factors. Fifth, we construct an emotion factor and assess whether well-known factors can explain it. Finally, we provide evidence from robustness checks.

We develop the market emotion index from news articles published in four widely circulated national newspapers and seventeen local newspapers in the U.S. We plot the market emotion index across time to observe whether it is capturing any significant stock market events that are expected to generate investor emotions. Figure 1 shows that during the sample period our market emotion index captures stock market event such as the financial crisis. The level of anxiety goes up during the crisis. Before the event, newspapers mostly produce news that induces excitement as the market emotion index reflects the positive trend during the formation of the crisis.

[Please insert Figure 1 here]

We also explore the relationship between emotion, mood, sentiment, uncertainty, and narrative tone betas. Table 1 reports the results of correlations. The emotion beta is not highly correlated with mood, sentiment, tone, and uncertainty betas. Among all betas, emotion beta has moderate correlation (0.268) with mood beta which is completely plausible as mood is essentially incidental emotion that indirectly affects investors' integral emotions. To disentangle the impact of incidental emotions from our integral emotion beta measure that drives investors' decision-making, we control for mood beta in the Fama-MacBeth regressions. With a variety of other incidental sentiment measures such as Baker and Wurgler (2006) investor sentiment, and University of Michigan's consumer confidence index, our emotion beta shares low correlation. We also observe very low correlation between emotion and valence-based positive/negative tone betas—Loughran and MacDonald (2011) and Henry (2008). Our conditional emotion beta represents the emotional utility investors derive while engaging in investment decision making that drives the demand and supply of the stocks in the stock market. On the contrary, a valence—either positive or negative—produces two completely opposite reactions (see, for example, Lerner and Keltner, 2000, 2001) that dilutes the strength of valence to affect decision-making. Emotion beta also shares a low correlation with economic uncertainty beta of Bali et al. (2017) which is derived using one-month ahead uncertainty index of Jurado et al. (2015) and economic policy uncertainty beta generated using Baker, Bloom, and Davis's (2016) economic policy uncertainty index. Thus, the correlation coefficients among all the beta measures indicate that emotion beta, a distinct manifestation of integral emotions, is different from the mood, sentiment, uncertainty, and tone betas.

[Please insert Table 1 here]

4.1 Fama and MacBeth regressions

We start by examining the cross-sectional relation between the emotion beta and expected returns at the stock level using Fama and MacBeth (1973) regressions. We present the time-series averages of the slope coefficients from the regressions of one-month-ahead stock excess returns on emotion sensitivity (β^{MEI}) after controlling for well-known predictors of the cross-section of stock returns. The monthly cross-sectional regression is run for the following specification:

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

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). The cross-sectional regression uses monthly frequency from January 1995 to December 2018.

[Please insert Table 2 here]

Panel A of Table 2 reports Fama-MacBeth time-series averages of the slope coefficients and the Newey-West t-statistics in parentheses. We find a positive and statistically significant relation between emotion beta and cross-section of future stock returns even in the presence of all other control variables. Higher emotion beta earns higher returns. The emotion sensitivity measure has an estimate of 0.55 with a t-statistic of 4.06 (see, Column 6) and imply that higher emotion beta earns higher future stock returns. In economic terms, a one-standard-deviation shift in emotion beta is associated with a 1.35% [= 0.55 × 2.45] shift in the stock excess return in the following month.

In Panel A of Table 2, the average slope from the monthly regressions of realized excess returns on β^{MEI} after controlling for the market factor, in Column 2, is 0.83 with a Newey-West t-statistic of 3.48. To determine the economic significance of this average slope coefficient, we use the average values of the emotion sensitivities in the quintile portfolios. Table 3 shows that the difference in emotion sensitivity between high-minus-low quintile portfolios is 0.76 [= 0.79 – 0.03] per month. If a stock were to move from the lowest to the highest quintile of β^{MEI} the change in the stock's average expected return would be a significant increase of 0.68% [= 0.90 (see, Column 1) × 0.76] per month. In Table 2, columns two to six controls for other predictors and still the average slope coefficient of β^{MEI} default is positive and significant. The results are similar after controlling for industry effects. Overall, the results are consistent with our first hypothesis that emotion beta positively predicts the cross-section of stock returns and the argument that investors' integral emotions and associated object-relationships with stocks can help explain return variation in the cross-section and the effect is distinct from other well-known factors.

In Panel B of Table 2, we examine the long-term predictability of the emotion beta and find that the positive relation between emotion beta and future stock returns extends beyond one-month. The Fama-MacBeth regression results show that after controlling for different firm characteristics and risk factors, the average slopes on emotion beta remains positive and economically significant up to eight-months in the future. The significance of emotion beta disappears when predicting nine-month-ahead returns and beyond.

4.2 Univariate portfolio-level analysis

To provide further evidence in favor of our conjecture, and to account for differences in emotion beta portfolios, we examine the predictability and risk-adjusted performance of emotion-based trading strategies using different factor models. In particular, we create quintile portfolios and compute equal and value-weighted portfolio returns. Portfolios are rebalanced each month.

Table 3 reports the emotion beta portfolio characteristics. The size (market capitalization in millions of dollars) of the different quintiles monotonically decreases from low emotion beta portfolio to high emotion beta portfolio. High emotion beta stocks have lower book-to-market (B/M) than low emotion beta stocks. Small growth stocks are more emotion sensitive than large value stocks. High emotion beta firms also have higher gross profitability (GP), growth in assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and lottery-like features (MAX). Across all the characteristics the high emotion-beta portfolio of stocks is significantly different from low emotion-beta portfolio of stocks. The nature of these stocks makes them ideal to grab investor attention and derive emotion utility from. Specifically, we conjecture that investors find high emotion-beta stocks to have emotional glitter as their valuations are highly subjective that can create temporary price pressure leading to a short-lived mispricing in the stock market.

[Please insert Table 3 here]

Panel A of Table 4 reports the portfolio average excess returns. Specifically, we examine whether high-minus-low emotion beta portfolios generate average excess returns across different return adjustment models. we adjust stock returns for characteristics, market, and industry returns. First, we present raw average excess returns. Second, we adjust characteristics-adjusted return and generate returns following Daniel, Grinblatt, Titman, and Wermers (1997, DGTW). Third, we adjust market returns and use value-weighted index returns as the market return. Finally, we adjust Fama-French 48-industry returns. For each month, we form quintile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the past month. All four columns in Table 4 present the average excess returns on the value-weighted portfolios, and the last row reports the high-minus-low portfolio's average excess returns. In line with our main conjecture, we find that investors can earn economically significant average excess returns of 0.54-0.55% (t-statistics ranging from 2.42 to 3.80) by going long (short) in the undervalued (overvalued) high (low) emotion beta portfolios. Investors feel the emotional charge and derive emotional utility from high emotion-beta stocks that influence their investment decisions accordingly.

[Please insert Table 4 here]

Next, we examine the ability of the emotional trading strategies to generate economically significant alphas. Panel B of Table 4 reports the univariate portfolio results. For each month, we again form quintile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}) during the previous month. The columns of Panel B of Table 4 presents risk-adjusted abnormal returns (alphas) from two different factor models: (i) α_5 is the intercept from the regression of the excess portfolio returns on a constant, market (MKT), size (SMB), value (HML), operating profitability (RMA), and investment (CMA) factors; and (ii) α_7 is the alpha relative to the market (MKT), size (SMB), value (HML), momentum (MOM), operating profitability (RMA), investment (CMA), and liquidity (LIQ) factors.

As shown in the second column of Table 4 Panel B, for the equal-weighted portfolio, α_5 increases almost monotonically from 0.15% to 0.56% per month. The difference in alphas between the high-β^{MEI} quintile and low-β^{MEI} quintile portfolios is 0.41% per month (or 5.03% per annum) with a Newey-West t-statistic of 5.23. The last column for the equal-weighted portfolio present similar alpha results from alternative factor model. The difference in alphas between high-β^{MEI} and low-β^{MEI} portfolios is α_7 = 0.42% per month (t-stat. = 5.15) for the seven-factor model. The significant alphas indicate that after controlling for the well-known factors, the return difference between the high-β^{MEI} and low-β^{MEI} stocks remain positive and statistically significant. The last two columns of Table 4 Panel B present evidence from the value-weighted portfolios of β^{MEI}. Consistent with the results of equal-weighted portfolios, the value weighted alpha differences between the high-β^{MEI} and low-β^{MEI} portfolios are also positive and significant: α_5 = 0.49% per month (t-stat. = 2.74); and α_7 = 0.46% per month (t-stat. = 2.59).

The evidence and results we present are in favor of our key conjecture that high emotion beta stocks earn higher returns than low emotion beta stocks do. The high-quintile emotion beta stocks are small growth stocks that are risky and open to subjective valuations. Investors because of the intensity of integral emotions and associated object-relationships with these stocks feel emotions of excitement as well as anxiety for future uncertainty and expect higher average excess returns that leads to economically significant alphas.

4.3 Conditional factor models

Next, to allow for time-varying exposures to systematic risks, we account for portfolio risk using various conditional factor models. We include a number of conditional macroeconomic factors that vary with the U.S. business cycle and estimate portfolio alpha. Specifically, we interact each return factors used in estimating alpha 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 prolonged recession period following the up and down phase of the dot.com bubble and financial crisis following Taffler et al. (2021); (ii) the *cay* residual of Lettau and Ludvigson (2001); (iii) the paper bill spread which is the difference between commercial paper yield and 30-day Treasury bill rate; (iv) the term spread which is difference between 10-year and 1-year government bond yield; and (v) the default spread which is the difference between BBB and 1-year government bond yield.

We report the conditional alpha estimates and factor exposures in Table A2. Each individual column of Table A2 controls for Fama-French factors, LIQ, and their interaction with each U.S. systematic risk factors. The last column includes 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 differences between high and low quintiles. We find that even after controlling for other conditional factors the high-minus-low portfolio alpha is economically significant across models and weightings. For example, the high-minus-low emotion beta portfolio alpha when we use the conditional model with the NBER Recession interaction and the *cay* residual are 0.41% and 0.45% with a *t*-statistics of 2.09, and 2.35 respectively (Panel B Columns 1 and 3). The alpha remains significant when we control for all the time-varying U.S. systematic risks simultaneously. These estimates are qualitatively similar to the unconditional five- and seven-factor model alpha estimates of 0.49% and 0.46% (Table 4 Columns 4 and 5). Taken together, these conditional factor model estimates are similar to results from unconditional models and provide evidence in favor of our conjecture that the higher the emotional charge/beta the higher the stock return.

4.4 Emotion beta persistence and alpha longevity

The emotion sensitivities we document in Table 4 are for the portfolio formation month and, not for the subsequent month over which we measure the average return. Investors earn higher abnormal return for high emotion beta stocks in the next month but will this pattern persist in the future, if persists then for how long.

We examine for persistence by running cross-sectional regressions of β^{MEI} on the previous twelve-month's β^{MEI} and lagged cross-sectional predictors. Specifically, for each month we run a regression across firms of 1-year ahead β^{MEI} on lagged β^{MEI} and lagged cross-sectional return predictors – the market beta (β^{MKT}), the market capitalization (Size), volatility beta (β^{VIX}), the book-to-market ratio (BM), the momentum (MOM), the short-term reversal (REV), the illiquidity (ILLIQ), the idiosyncratic volatility (IVOL), the annual growth in book assets (I/A), the operating profitability (ROE), and the lottery demand (MAX). Panel A of Table 5 presents the univariate regression of β^{MEI} on previous twelve-month's β^{MEI}; the coefficient is large and statistically significant. It implies that stock with high β^{MEI} tend to exhibit similar feature in the following twelve months. After adding the cross-sectional return predictors, the coefficient remains large and significant. β^{MEI} remains highly persistent up to sixty-months in the future demonstrating the power of integral emotions in driving investor behavior.

[Please insert Table 5 here]

Next, we examine the performance of the high-minus-low portfolio as the gap between portfolio formation and emotion beta-based portfolio return estimation increases. If the abnormal performance of the high-minus-low portfolio reflects emotional charge induced mispricing that eventually gets corrected, the performance estimates would become weaker as the lag increases. Panel A of Figure 3 shows the effect of varying portfolio formation from 1 to 12 months on monthly seven-factor abnormal returns. A positive shift in portfolio formation period corresponds to delayed formation of the high-minus-low portfolios. As the gap increases the abnormal return becomes weaker both in terms economic and statistical significance. This evidence shows that the abnormal return of high emotion beta stocks is corrected in four-months by the market. In Panel B of Figure 3, we vary the holding period of the high-minus-low emotion beta-based portfolio. Specifically, we hold emotion sensitive hedge portfolio for 3, 6, and 12 months and rebalance portfolios accordingly. Similar, to the findings we detect in Panel A, we find for holding periods of more than 3-months the high-minus-low trading strategy does not produce any alpha. There can be two possible explanation for such correction. First, it is likely that the mispricing is generated by investor inattention that gets corrected. Second, investors can reframe and reappraise the emotional stimulus to reduces the intensity of the emotional responses (Gross, 2002) that weakens then impact of emotions on asset prices. The mispricing disappears completely after four months.

[Please insert Figure 3 here]

4.5 Is emotion beta capturing mood? Or sentiment? Or economic uncertainty? Or policy uncertainty? Or tone? [after conditional]

4.5.1 Is emotion beta capturing mood?

We examine, here, if the findings are sensitive to mood. So far, we always use emotion sensitivity. However, it can cast doubts in our mind that emotion is capturing different types of mood. To provide evidence that our emotion beta is different from mood, we first estimate mood beta. To estimate mood beta, we estimate the following 10-year rolling window regression following Hirshleifer et al. (2020). We estimate mood beta for each stock from a time-series regressions of stock's excess returns earned during prespecified and realized high and low mood months ($R_{i,MoodMonth}$) on the contemporaneous equal-weighted CRSP excess returns ($XRET_{A,MoodMonth}$).

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

where, $\beta_{i,month}^{Mood}$ is the mood beta. The regression includes eight months in a year: four prespecified (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) use January and March as prespecified high mood period and September and October as low mood period based on SAD effect defined by Kamstra et al. (2003).

Table 6, Column 1 reports the results of cross-sectional Fama-MacBeth regression after controlling for mood beta, firm characteristics and other risk-factors. Even after accounting for mood beta β^{MEI} produces a significant coefficient with a *t*-statistic of 2.29. In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 1.13% [= 0.46 (see, Column 1) × 2.45] shift in the stock's excess return in the following month. The result is not surprising because both, emotion and mood, betas are capturing completely different ingredients of decision making. Mood is by definition unrelated to the decision at hand whereas emotion is integral and specific to a decision.

[Please insert Table 6 here]

It arguable that emotion may have low or no predictability during high and low mood period because during these periods, as empirical evidence shows (see, Hirshleifer et al., 2020), high (low) mood positively (negatively) predicts stock returns. To counter this argument, we rerun the Fama-Macbeth regressions during high (low) mood period and the present results in Table 7. The mood betas as expected have positive (negative) predictability. Interestingly, our emotion beta during these periods still show predictability (coefficient of 2.15 and 1.09 with a *t*-statistics of 6.09 and 2.94). Thus, empirical evidence, we provide, show that emotion beta has incremental predictive power to explain the variation in the cross-section of future stock returns.

[Please insert Table 7 here]

4.5.2 Is emotion beta capturing sentiment?

Next, we argue that our emotion beta is distinct from different sentiment measures. We estimate two sentiment betas by estimating two 60-month rolling window regressions for each stock's excess returns on Baker and Wurgler (2006)[12] investor sentiment orthogonalized for macro-variables, and University of Michigan's consumer confidence index (UMCCI)[13] and Fama-French three factors separately.[14]

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{SENT} SENT_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \varepsilon_{i,t} \quad \dots \quad (8)$$

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

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

[14] In an unreported test, we also estimate manager sentiment beta using manager sentiment index of Jiang et al. (2019). The index is based on positive and negative tones of conference calls and financial statements. The index is available for a period of 12 years (2003-2014) and as we need to run a rolling regression of 60-months to get beta we are left with only 7 years of data. Because of the relative short length of the data, we do not report its results. However, our results remain unchanged when we control for manager sentiment beta.

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{UMCCI} UMCCI_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \varepsilon_{i,t} \quad \ldots \quad (9)$$

where, $\beta_{i,t}^{SENT}$ is the Baker and Wurgler, and $\beta_{i,t}^{UMCCI}$ is the University of Michigan consumer confidence beta.

Table 6 Column (2), and (3) presents Fama-MacBeth regressions after controlling for different sentiment betas. In the presence of different sentiment betas, the emotion beta shows incremental economically significant predictive ability with coefficients of 0.46, and 0.49 and *t*-statistics of 3.65, and 3.91 respectively. Thus, we can conclude that emotion beta is different from sentiment betas and adds to the literature by explaining the variation in the cross-section of expected stock returns.

4.5.3 Is emotion beta capturing uncertainty?

It is arguable that economic uncertainty drives our results as high-(low-)levels of uncertainty may arouse negative (positive) sentiment. To counter this line of argument, we control for uncertainty beta of Bali et al. (2017) which is derived based on one-month ahead economic uncertainty index of Jurado et al. (2015). We estimate uncertainty beta by estimating 60-month rolling window regression for each stock's excess returns on uncertainty index, size (SMB), value (HML), momentum (MOM), liquidity (LIQ), investment (I/A), and profitability (ROE).

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{UNC} UNC_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \beta_{i,t}^{4}.MOM_t + \beta_{i,t}^{5}.LIQ_t + \beta_{i,t}^{6}.I/A_t + \beta_{i,t}^{7}.ROE_t + \varepsilon_{i,t} \quad \ldots \quad (10)$$

where, $\beta_{i,t}^{UNC}$ is uncertainty beta. We estimate the Fama-MacBeth regression of a stock's excess return on the previous month's emotion beta and controlling for uncertainty beta (β^{UNC}). The policy uncertainty beta is estimated by running a 60-month rolling window regression for each stock's excess returns on economic policy uncertainty index and Fama-French three factors.

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{EPU} EPU_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \varepsilon_{i,t} \quad \ldots \quad (11)$$

where, $\beta_{i,t}^{EPU}$ is the policy uncertainty beta. Using the uncertainty betas, we estimate the Fama-MacBeth regression of a stock's excess return on the previous month's emotion beta, uncertainty betas, and lagged control variables.

Table 6 Columns (4) and (5) presents Fama-MacBeth regressions after controlling for uncertainty betas. The emotion beta has incremental predictive ability with coefficients of 0.43 and 0.42 and *t*-statistics of 3.36 and 3.38. Thus, we can conclude that emotions we are capturing beta is different from uncertainty-driven negative sentiments.

4.5.4 Is emotion beta capturing tone?

We further argue that our emotion beta is distinct from popular text-driven tone measures. We use positive/negative word dictionaries of Loughran and MacDonald (2011) and Henry (2008) to construct two tone measures using equation (2) and same news articles we use to derive *MEI*.[15]

To provide evidence that our emotional measure is distinct from tone, in Table A5, we first present the top ten emotional and tonal words. In case of excitement and positive words, only "boost" and "confident" are common while "fear" and "volatile" are common between anxiety and negative words. The top ten counts primarily show that the two dictionaries, emotion and tone, are capturing totally different sense. Second, in Table A6, we show the distribution of news articles across *MEI* and tone quintiles. If both the *MEI* and tone are measuring the same thing then all the diagonal elements should account for most of the news items. However, we find the off-diagonal elements are of sizable amount that indicates the variation in articles the two measure utilize to produce scores.

Third, to reinforce further our point, we present two sample news articles that have totally different emotional and tonal scores (see Appendix 2). The news articles have completely different emotional scores whereas tone remains neutral. The first article is from *The New York Times* (date: February 28, 2012) and on average it elicits excitement as the market emotion index score is 0.50. However, the LM tone is neutral with a score of 0.0. The careful analysis of the article shows that the stock market is doing well that investors interpret as exciting and use as source to base their economic decisions. The second article is from *Wall Street Journal* (date: October 06, 2007). Again, by reading the news investors' feel anxiety and market emotion index correctly derives a score of -0.40. However, tone remains neutral. The

[15] The LM tone is $LM_t = \frac{Positive_t - Negative_t}{Positive_t + Negative_t}$ and Henry tone is $Henry_t = \frac{Positive_t - Negative_t}{Positive_t + Negative_t}$ where, $Positive_t$, $Negative_t$ are the number of positive and negative word counts during month t.

news articles analysis show emotion and tone are capturing different vibes and emotion is independent of tone.

Finally, we also estimate the tone beta using the following specifications and examine whether emotion beta 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 tone and Henry tone after controlling for Fama-French three factors.

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{LM} LM_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \varepsilon_{i,t} \ \ldots \ (12)$$

$$R_{i,t}^{e} = \alpha_i + \beta_{i,t}^{Henry} Henry_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t + \varepsilon_{i,t} \ \ldots \ (13)$$

where, $\beta_{i,t}^{LM}$ and $\beta_{i,t}^{Henry}$ are the two-tone betas. Using the sensitivity, we estimate the Fama-MacBeth regression of a stock's excess return on the previous month's conditional emotion beta, tone sensitivities, and lagged control variables.

Table 6 columns (6) and (7) report the results of cross-sectional regression considering all the tone betas. Even after accounting for LM and Henry tone measures β^{MEI} produces a significant coefficient. In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 1.13% [= 0.46 (see, Column 4 and 5) × 2.45] shift in the stock's excess return in the following month. Emotion sensitivity complements tone betas and is certainly capturing something different than LM and Henry's positive/negative tone.

Taken together, we find economically significant predictive ability of emotion beta when we include all the mood, sentiment, tone, and uncertainty betas together in a multivariate Fama-MacBeth regression (see Column (8) and (9)). All along we discover the enormous strength distinct investor emotions possess in terms of explaining the variation in cross-section of future stock returns.

4.6 Bivariate portfolio-level analysis

This section examines the relation between emotion beta and future stock returns by performing bivariate portfolio sorts. First, we focus on average emotion beta across two prominent cross-sectional return predictors – market capitalization (SIZE) and book-to-market (B/M). We form quintiles based on SIZE and then, within each SIZE quintile, we sort stocks into further quintiles based on B/M so that quintile 1 (quintile 5) contains stocks with the lowest (highest) market capitalization and book-to-market values. Table A3 presents the average emotion beta across the bivariate quintiles. Stocks with small market capitalization are more emotion sensitive than that of stocks with large market capitalization. Growth stocks are more emotion sensitive than value stocks. Interestingly, small growth stocks are more emotion sensitive to large value firms and these are hard to value stocks that should drive the high-minus low average excess returns and alphas.

Next, we examine the relationship between emotion beta and future stock returns after controlling for different firm characteristics. Specifically, we perform bivariate portfolio-level analysis of emotion beta stocks with respect to four firm characteristics – market capitalization (Size), book-to-market (B/M), gross profitability (GP), and annual growth of book assets (I/A). Table A5 reports the results of the conditional bivariate sorts between a firm characteristic and emotion beta. We report both equal- and value-weighted alphas relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors.

We condition on the market capitalization (SIZE) by forming quintile portfolios based on SIZE. Then, within each SIZE quintile, we further sort stocks based on emotion beta (β^{MEI}) into quintile portfolios. We average portfolio returns across five SIZE quintiles to produce quintile portfolios with dispersion in β^{MEI} but that contain stocks across all market capitalization (see Bali et al. 2017). This process creates a set of β^{MEI} portfolios with very similar levels of market capitalization, and hence control for differences in SIZE. The first column in Panel A of Table A4 shows that after controlling for SIZE, the equal-weighted difference in the abnormal return spread between high and low emotion beta small stocks is 0.43% per month with a t-statistic of 4.82. We find similar results using value-weighted portfolio returns (see Column 1 in Panel B of Table A4). Thus, we find that size does not explain the high (low) returns earned by the high (low) emotion sensitive stocks.

We repeat the same procedure with book-to-market, gross profitability, and annual growth in assets. After controlling for all these firm characteristics, we find that the high minus low emotion beta trading strategy produces positive and significant alphas as we use equal- and value-weighted portfolio returns. The results, we report, indicate that well-known cross-sectional return predictors cannot explain the unique emotion beta premium.

4.7 Equity portfolios as test assets

We have presented evidences until now to demonstrate the role emotion beta plays in predicting the cross-sectional variation in individual stock returns. Now, we proceed by introducing emotion beta as a factor and examine the ability of well-known factors to explain the returns associated with the emotion beta. We form the emotion beta factor following Daniel et al. (2020). At the end of each month, we divide firms into two size groups (small "S" and big "B") based on firm's market capitalization is below and above the CRSP median breakpoint. Independently, we sort firms into one of the three emotional groups (low "L", middle "M", or high "H") based on firm's conditional emotion beta using the CRSP 20th and 80th percentile values of β^{MEI}. We form six portfolios (SL, SM, SH, BL, BM, and BH) based on the intersections of size and emotion beta groups. The emotion beta factor (EBF) returns each month is calculated as average return of the value-weighted high emotional portfolios (SH and BH) minus average return of the value-weighted low emotional portfolios (SL and BL), i.e., $EBF = (r_{SH} + r_{BH})/2 - (r_{SL} + r_{BL})/2$.

Table 8 shows that the value-weighted emotion beta factor generates an average monthly return of 0.44% with a Newey-West t-statistic of 2.62. We also estimate the alpha of the emotion beta factor using different factor models. The alphas remain positive, ranging from 0.30% to 0.66%, and significant with t-statistics ranging from 2.94 to 4.13. We find qualitatively similar results for when emotion beta factor is constructed with equal-weighted returns. As shown in the second row of Table 8, the equal-weighted emotion beta factor generates an average monthly return of 0.81% with a t-statistic of 4.92 and the alphas remain economically meaningful and statistically significant. These results indicate that well-known risk factors cannot explain the emotion beta factor.

[Please insert Table 8 here]

Due to the extensive research on cross-section of expected returns, Harvey et al. (2016) suggests that a five percent level of significance for a new factor is too low a threshold and argue for more stricter requirements with a t-statistic greater than 3.0. As shown in Table 2, the Fama-MacBeth cross-sectional regressions indicates that the emotion beta factor passes the hurdle with a t-statistic of 3.49 (3.85 controlling for industry effects), and just drops below this level controlling for momentum. Sorting stocks based on the intersection of size and emotion beta, we find in Table 8 that the equal-weighted (value-weighted) emotion beta passes the test with a *t*-statistic of 4.92 (2.62). This result, drawing on the sentiment literature that focuses on equal-weighted portfolios as sentiment mostly affects small stocks (Baker and Wurgler, 2006), is significant. We also provide comprehensive evidence that our results emotion beta-based return predictability is different from mood, sentiment, uncertainty, and tone. We also present evidence in subsequent robustness tests that our results are not driven by microcap stocks, and survives in the cross-section of large, liquid, and S&P 500 stocks. More importantly, the pricing ability of emotion beta factor is motivated by psychology-based emotion-imbued choice model and object relations theory and hence is subject to a lower hurdle.

4.8 Robustness checks

We provide a set of robustness checks in this section. First, we test whether alternative measures of the emotion sensitivity predict future stock return. Second, we examine whether microcaps drive our results since there are plenty of evidence that small stocks drive mispricing (see, for example, Baker and Wurgler, 2006). Third, we investigate whether the trading strategy is robust for S&P 500, largest 1000, and most liquid 1000 stocks. Fourth, we use different variations of market emotion index. Fifth, we also test whether excitement and anxiety capture different types of mispricing. Further, we analyze whether the asymmetric or valency of emotion beta captures similar mispricing providing evidence in favor of our choice of focusing on the strength of emotion beta rather than its direction.

4.8.1 Alternative measures of emotion beta

For the baseline analysis, we control Fama-French three factors to generate emotion beta using equation (5). It is possible to argue that with different set of control variables we may find no mispricing and predictability as we have degrees of freedom with respect to choosing the right-hand side variables. To examine such possibility, in this section, we use three alternative measures of β^{MEI} by first controlling only for the market (MKT) factor, second the market (MKT), size (SMB), value (HML), and momentum (MOM) factors, and third, following Bali et al. (2017) the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors.

$$\text{Model 1: } R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{a}} + \beta_{i,d}^{1}.MKT_t + \varepsilon_{i,t} \quad \dots \qquad (14)$$

$$\text{Model 2: } R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{b}} + \beta_{i,d}^{1}.MKT_t + \beta_{i,t}^{2}.\mathrm{SMB}_t + \beta_{i,t}^{3}HML_t + \beta_{i,t}^{4}MOM_t + \varepsilon_{i,t} \quad \dots \text{ (15)}$$

Model 3: $R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{c}}.MEI_t + \beta_{i,t}^{1}.MKT_t + \beta_{i,t}^{2}.SMB_t + \beta_{i,t}^{3}.HML_t$

$$+\beta_{i,t}^{4}.MOM_t + \beta_{i,t}^{5}.IVA_t + \beta_{i,t}^{6}.ROE_t + \beta_{i,t}^{7}.LIQ_t + \varepsilon_{i,t} \quad \ldots \qquad (16)$$

After generating the $\beta^{MEI^{a}}$, $\beta^{MEI^{b}}$, and $\beta^{MEI^{c}}$ from these three specifications, we form equal-weighted and value-weighted portfolios and compute average excess returns and factor alphas for each quintile. Panel A, B, and C of Table 9 shows that β^{MEI} with both Models 1, 2, and 3 produce a positive and significant alpha for both equal and value-weighted portfolios. The results presented in Table 9 along with those reported in Table 6 indicate that emotion beta, even with alternative measures, remain a significant predictor of future stock returns.

[Please insert Table 9 here]

4.8.2 Are small stocks driving the alpha? Does emotion beta premium survive across different stock subsamples?

We control for microcaps as small firms exhibit high emotion beta and to evidence that the main results are not driven by microcaps. We follow the definition of Ball et al. (2020) and only include stocks with market values of equity at or above 20^{th} percentile of the market capitalization. Table 10 presents the results of emotion beta univariate portfolios. Not surprisingly, the high-minus-low strategy produce a positive and significant average excess return and alphas for both equal and value-weighted portfolios (see Column 2 of Panel A). The mispricing identified by the emotion beta is a universal phenomenon and is not affected by microcap stocks.

[Please insert Table 10 here]

We also investigate if emotion beta premium is driven by small, illiquid, and low-priced stocks. Specifically, we test whether emotion beta generates premium for S&P 500, largest 1,000 stocks based on market capitalization, and 1,000 most liquid stocks based on Amihud's (2002) illiquidity measure. Columns (3) to (5) of Table 10 present the seven-factor alpha (α_7) spread between the high-β^{MEI} and low-β^{MEI} portfolio is 0.48% per month (t-statistic = 2.75) for the S&P 500 stocks, 0.42% per month (t-statistic = 2.70) for the largest 1,000 stocks, and 0.39% per month (t-statistic = 2.41) for the 1,000 most liquid stocks. Hence, we conclude that the emotion premium is not exclusive to small, illiquid and low-priced stocks.

4.8.3 Alternative market emotion index

We also use several variations of market emotion index to estimate the emotion beta and test the performance of high-minus-low emotion beta-based trading strategy. First, we use standardized market emotion index that have a mean of zero and standard deviation of one. Second, we use a time weight where MEI at day *d* receives more weight than MEI of day *d-1*. Thus, we compute the monthly MEI by weighting daily MEI by their respective time-weights (Time-weighted $MEI_t = \sum_{d=1}^{t} MEI_d \times weight_d$). Third, we generate 'Total MEI' calculated as the ratio of sum of excitement and anxiety words to total words in a month ($Total\ MEI_t = \frac{Excitement_t + Anxiety_t}{Total\ Words_t}$). Fourth, we also use 'Net MEI' is calculated as the ratio of the difference between excitement and anxiety words to total words in a month ($Net\ MEI_t = \frac{Excitement_t - Anxiety_t}{Total\ Words_t}$).

Panel B of Table 10 presents the results using different variations of market emotion index. The high-minus-low strategy produces a positive and significant alpha across irrespective of the MEI measure for both equal and value-weighted portfolios (see Columns (2)-(5) of Panel B). The results show that emotion beta-based mispricing is robust and does not depend on the measurement of market emotion index.

4.8.4 Valency-based emotion premium

In all the analysis until now, we use absolute beta from equation (5). The main impetus for not choosing asymmetry in emotion beta is emotional charge. We assert that instead of affect, i.e., goodness and badness or positivity and negativity, investors are in general prone to the sheer burst they feel once they receive information. Alongside, trend chasers and contrarians will be more active during the bullish and bearish period that will create temporary price pressure. To provide evidence in favor of using absolute emotion beta, we split the sample based on asymmetric emotion beta and test whether high-minus-low emotion beta-based trading strategy still earn economically significant alpha.

Specifically, at first, we take above the median of the asymmetric beta which are essentially large positives. Next, we sort the stocks in ascending order into quintiles where high (low) portfolio contains most (least) positive emotion beta stocks. Table 10, Panel C Column (2), provides results of univariate sorting based on above median emotion betas. We find that high-minus-low trading strategy generates economically significant alpha after controlling for well-known asset-pricing factors. Next, we take below the median of the asymmetric beta which are essentially large negatives and sort the stocks in descending order into quintiles where high (low) portfolio contains most (least) negative emotion beta stocks. Table 10, Panel C Column (3), provides results of univariate sorting based on highly negative emotion betas. Again, the high-minus-low trading strategy generates economically significant alpha.

Next, we examine whether excitement and anxiety we use to generate the market emotion index capture different sources of mispricing owing to emotional valency. we estimate the excitement beta using equation (5) where we use 'Excitement' as the proportion of excitement words scaled by total words in a month. We repeat the same for estimating anxiety beta. Panel C, Columns (4) and (5), of Table 10 shows results based on excitement and anxiety beta. Irrespective of the valence of the emotion, we find qualitatively similar results to that reported in Table 6.

Taken together, the results from Panel C of Table 10 provides important evidence on behalf of our assertion that investors act basing on emotional charge rather than relying solely on affect. Thus, our absolute emotion beta measure correctly identifies investors' emotional sensitivity toward stocks that create mispricing in the broad cross-section of the U.S. stock market.

4.8.5 Extreme portfolio alpha

In all our portfolio level analysis we construct quintile portfolios. One can always argue that the mispricing we document is more pronounced with quintile portfolios. Here, we construct a series of Long-Short portfolios ranging from tercile to decile. Figure 2 presents extreme portfolio alphas. For each Long-Short portfolio alpha we control seven factors: the market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ). Across all portfolios the Long-Short generates economically and statistically significant alpha estimates. The alpha estimates and their associated *t*-statistics indicate that our result is not driven the choice of the number of portfolios constructed based on previous months emotion beta.

[Please insert Figure 2 here]

Overall, all robustness checks support our main hypothesis that high emotion beta stocks generate high stock returns compared to low emotion beta stocks. All the results with alternative sensitivity specifications, different stock subsamples, MEI measures concur with our main findings that emotion can predict cross-section of stock returns.

5. Conclusion

The influence of emotion in predicting stock returns has not received much attention. We provide some evidence that emotion matters and can explain the cross-section of stock returns using about sixty-thousand news articles from twenty-one national and local-level newspapers. Emotion beta causes divergence in prices from fundamentals due to the intensity of the integral emotion investors' feel and develop associated objection-relations that overrides rational decision making (Loewenstein et al., 2001) and individuals tend to make satisfying rather than optimal decisions (Simon, 1955; Conlisk, 1996).

In this paper, we find that investors integral emotions reflected by the news articles predict the cross-section of stock returns. We capture investors integral emotions using a novel method and identify different emotional stock portfolios. Stocks with high emotion beta earn a higher average excess return than low emotion beta stocks. A high-minus-low trading strategy generates an average excess return of 0.54% per month during the estimation period. Both the emotion in decision making and object-relations theory explain the results. Investors feel specific emotions during the investment decision which is intensified by the news stories about the state of the stock market and because of the emotional intensity investors create an emotional attachment with the stocks they invest in that drives the asset prices. Our emotion beta remains a significant predictor of future stock return up to eight-months into the future. The predictive ability of integral emotion beta is also distinct from that of incidental betas such as mood and sentiment, valence beta such as tone, and uncertainty beta. In addition, we find emotion sensitive mispricing is large and statistically significant for small growth stocks as their valuation depends on subjectivity. The intensified integral emotions fuel the subjective valuations and create mispricing. As a result, growth stocks dominate the much less prone to subjective valuation, i.e., value stocks in earning a higher average excess return. The emotion beta remains persistent up to the period of sixty-months indicating that the pattern has considerable longevity. However, high-minus-low trading strategy produces economically significant alpha up to four-months owing to investor unconscious emotion and inattention. As investors become more aware about emotional reaction and receive new information the mispricing ceases to exist. Our results are robust under different specifications to derive emotion beta and market emotion index. We find evidence of mispricing across a range of criteria such as in the absence of microcaps, and in S&P 500, 1000 largest, and most liquid stocks.

The results contribute to several strands of literature. First, the study contributes to the mood and asset pricing literature. We contribute by measuring emotion quantitatively and use its sensitivity to predict cross-section of stock returns. Second, the study also contributes to the news and finance literature as our emotional measure is derived from news articles. Specifically, we contribute by developing a market emotion index using textual analysis of news narratives on the state of the stock market published in the national- and local-level newspapers in the United States. Finally, we contribute to the emotion and decision-making psychology literature as we present economically and empirically robust results linking investors' unconscious integral emotions, i.e., needs and drives, to investment decisions.

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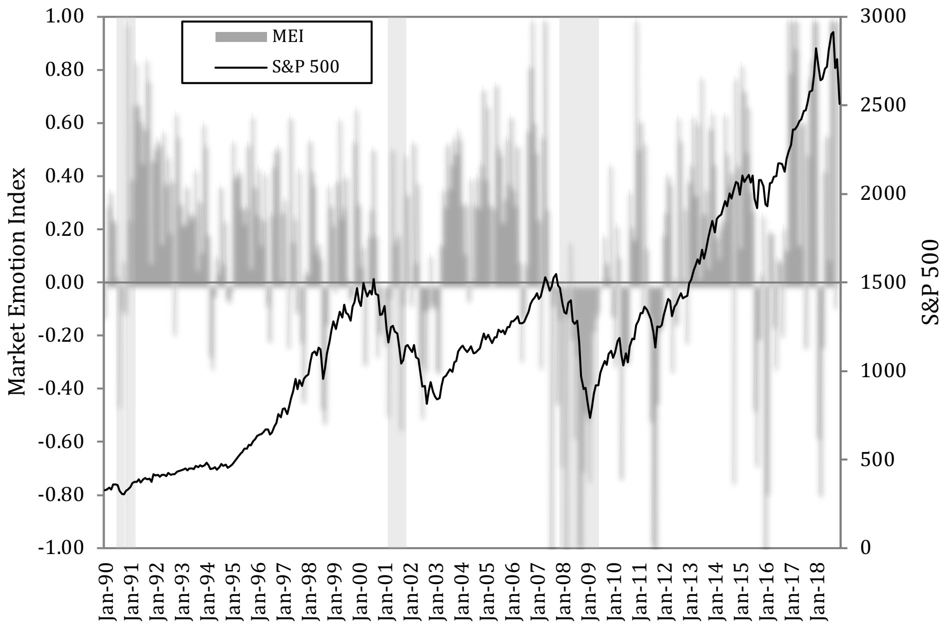

Figure 1: Emotion and S&P 500 index overtime. The figure shows the relationship between market emotion index (MEI) and S&P 500 index over time. Market emotion index is measured as the ratio of difference between excitement and anxiety to the total of excitement and anxiety word counts. We use news articles over a month to get the monthly word counts. Emotion fluctuates in conjunction with the S&P 500 index. During the financial crisis market emotion index is broadly negative. Before the crisis positive emotions help form the event. The shaded areas represent NBER recession periods. The sample period is from January 1990 to December 2018.

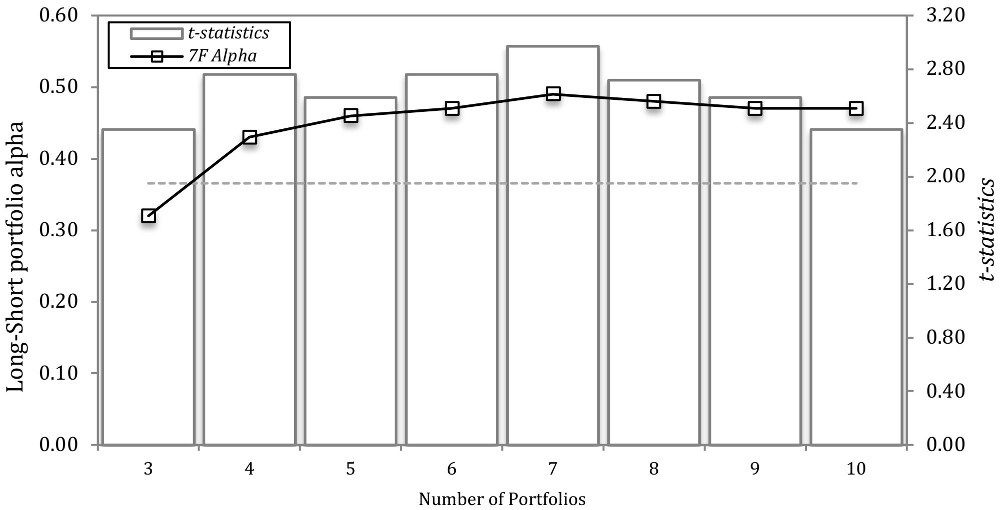

Figure 2: Extreme portfolio alpha. The figure presents a series of Long-Short trading strategy alpha estimates and their *t*-statistics of different portfolios formed on emotion beta (β^{MEI}). For each month, we form portfolios ranging from tercile to decile by sorting stocks based on their emotion 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 the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors. The dotted red line represents *t*-statistic at 95% confidence level. The estimation period is from January 1995 to December 2018.

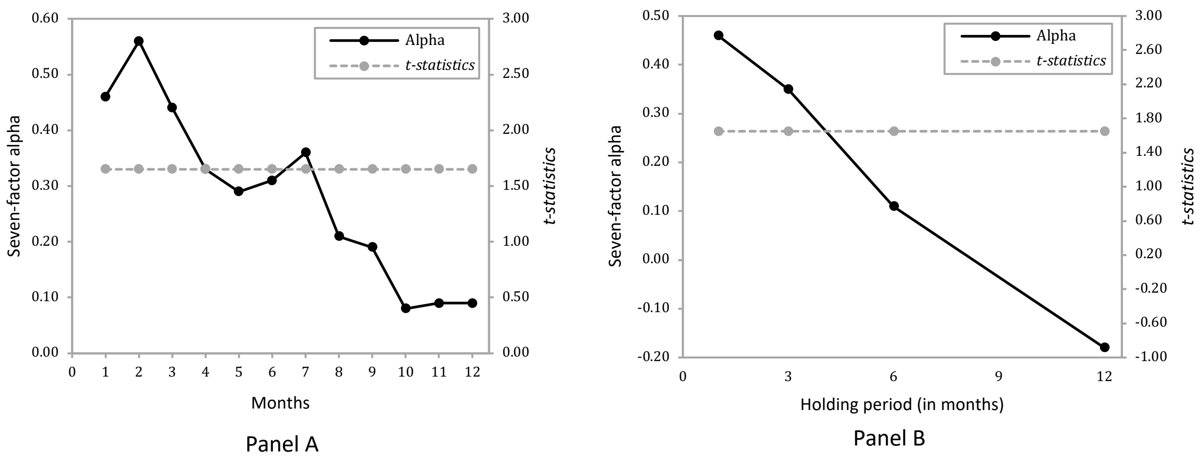

Figure 3: Longevity of alpha. The figure presents a series of Long-Short trading strategy alpha estimates of different portfolios formed on emotion beta (β^{MEI}). For each month, we form portfolios ranging based on their emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) β^{MEI} during the previous formation months. In Panel A, we examine the longevity of high-minus-low emotion beta-based trading strategy alpha estimates. We keep on increasing the gap between the portfolio formation and emotion beta portfolio return estimation from 1 month to 12 months. In Panel B, we hold emotion beta-based portfolios for different holding periods ranging from 3 to 12 months. The seven factor alphas are relative to the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors. The dotted red line represents t-statistic at 90% confidence level. The estimation period is from January 1995 to December 2018.

Table 1: Correlation between emotion, mood, sentiment, tone, and uncertainty betas. The table presents correlation between conditional emotion, mood, sentiment, tone, and uncertainty betas. The emotion beta (β^{MEI}) is derived by estimating a 60-month rolling regression of excess returns on market emotion index and Fama-French three-factors—market, size, and value. Then, we take the absolute value of β^{MEI}. The mood beta (β^{Mood}) (see, Hirsheifer, Jian, DiGiovanni, 2020) is computed by running a 10-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 two 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 a 60-month rolling regression of excess returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. By estimating a 60-month rolling regression of excess returns on University of Michigan's consumer confidence index and Fama-French three-factors, we generate the consumer confidence beta (β^{UMCCI}). By estimating a 60-month rolling regression of excess returns on LM and Henry tone and Fama-French three-factors, we generate the tone betas (β^{LM} and β^{Henry}). The tones are derived by taking the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and MacDonald (2011) and Henry's (2008) positive and negative dictionaries. The uncertainty beta (β^{UNC}) is computed by running a 60-month rolling regression of excess returns on Jurado et al.'s (2015) economic uncertainty index, MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. By estimating a 60-month rolling regression of excess returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index and Fama-French three-factors, we generate the economic policy uncertainty beta (β^{EPU}). The estimation period is from January 1995 to December 2018.

	β^{MEI}	β^{Mood}	β^{SENT}	β^{UMCCI}	β^{LM}	β^{Henry}	β^{UNC}	β^{EPU}
β^{MEI}	1							
β^{Mood}	0.268	1						
β^{SENT}	-0.065	-0.060	1					
β^{UMCCI}	-0.005	0.013	0.009	1				
β^{LM}	0.010	0.030	-0.016	0.309	1			
β^{Henry}	-0.013	0.017	0.028	0.348	0.696	1		
β^{UNC}	0.051	0.037	0.005	-0.074	-0.198	-0.159	1	
β^{EPU}	0.060	0.026	-0.082	-0.298	-0.339	-0.433	0.112	1

Table 2: Fama-MacBeth cross-sectional regressions.

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 Fama-MacBeth methodology. The control variables are the market beta (β^{MKT}), volatility beta (β^{VIX}), log 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). Panel B presents the results from regressing monthly excess returns in two- to 12-months ahead against β^{MEI} after controlling for all other predictive variables and for brevity, we do not report their intercepts, and coefficients. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Monthly Fama-MacBeth regressions

	Without industry effects						With industry effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β^{MEI}	0.90	0.83	0.80	0.52	0.47	0.55	0.77	0.73	0.70	0.41	0.39	0.45
	[3.49]	[3.48]	[3.37]	[3.09]	[3.46]	[4.06]	[3.85]	[3.94]	[3.71]	[2.80]	[3.12]	[3.65]
β^{MKT}		0.10	0.09	0.13	0.08	0.13		0.09	0.08	0.12	0.10	0.14
		[0.91]	[0.89]	[1.26]	[0.95]	[1.48]		[1.00]	[0.87]	[1.44]	[1.30]	[1.79]
β^{VIX}			-0.12	-0.32	-0.50	-0.31			-0.08	-0.27	-0.44	-0.28
			[-0.41]	[-1.23]	[-2.15]	[-1.40]			[-0.33]	[-1.22]	[-2.23]	[-1.51]
Size				-0.16	-0.18	-0.16				-0.15	-0.17	-0.16
				[-4.23]	[-4.96]	[-4.68]				[-4.28]	[-5.19]	[-4.90]
B/M				0.14	0.23	0.23				0.21	0.28	0.29
				[1.73]	[3.16]	[3.27]				[3.24]	[4.62]	[4.77]
MOM				0.07	-0.10	-0.11				0.05	-0.12	-0.13
				[0.34]	[-0.55]	[-0.58]				[0.27]	[-0.71]	[-0.71]
REV					-1.02	-1.18					-1.17	-1.34
					[-1.95]	[-2.24]					[-2.46]	[-2.76]
ILLIQ					-0.81	-0.90					-0.74	-0.83
					[-1.92]	[-2.12]					[-1.81]	[-2.01]
IVOL					0.07	0.41					0.05	0.41
					[1.29]	[5.94]					[1.15]	[6.55]
I/A					0.43	0.46					0.37	0.40
					[3.38]	[3.66]					[3.14]	[3.46]
ROE					1.46	1.43					1.55	1.52
					[5.73]	[5.85]					[6.64]	[6.67]
MAX						-0.28						-0.29
						[-4.74]						[-5.68]
Intercept	0.89	0.81	0.85	1.94	1.84	1.89	0.72	0.66	0.81	2.07	0.76	1.05
	[3.25]	[3.54]	[3.5961]	[5.22]	[5.08]	[5.30]	[2.08]	[2.16]	[2.67]	[5.17]	[2.59]	[4.23]
Adj. R-squared	0.56%	1.43%	1.75%	3.78%	5.76%	6.18%	4.50%	5.07%	5.38%	6.93%	8.56%	8.89%
N months	287	287	287	287	287	287	287	287	287	287	287	287

Panel B: Long-term predictive ability of emotion beta.											
n-months ahead	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$	$n = 9$	$n = 10$	$n = 11$	$n = 12$
β^{MEI}	0.38	0.25	0.40	0.33	0.22	0.37	0.36	0.21	0.33	0.32	0.19
	[3.17]	[2.24]	[3.33]	[2.79]	[1.98]	[3.32]	[2.52]	[1.50]	[2.47]	[1.65]	[1.32]
Firm controls & risk factors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	8.53%	8.39%	8.33%	8.32%	8.13%	8.09%	8.10%	8.10%	8.01%	8.02%	8.00%
N months	286	285	284	283	282	281	280	279	278	277	276

Table 3: Emotion beta portfolio characteristics.

The table reports the characteristics of portfolios sorted on emotion beta. For each month, we form quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. Columns two to seven present the average emotion beta (β^{MEI}), market beta (β^{MKT}), size (market capitalization in millions of dollars), book-to-market ratio (B/M), gross profitability (GP), annual growth of assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and demand for lottery-like stocks (MAX) across portfolios. The estimation period is from January 1995 to December 2018.

	Portfolios					
	Low	2	3	4	High	High-Low
β^{MEI}	0.03	0.09	0.16	0.27	0.79	0.76
						[15.83]
β^{MKT}	0.94	0.96	1.00	1.07	1.21	0.27
						[6.55]
Size	6,646.54	6,341.04	5,535.86	3,940.66	1,885.06	-4,761.48
						[-16.46]
B/M	1.24	1.24	1.23	1.18	1.01	-0.23
						[-6.30]
GP	0.35	0.35	0.36	0.37	0.37	0.02
						[4.36]
I/A	0.11	0.12	0.12	0.13	0.18	0.07
						[14.15]
IVOL	0.17	0.18	0.19	0.20	0.25	0.08
						[26.60]
ILLIQ	0.44	0.42	0.49	0.47	0.75	0.30
						[2.67]
MAX	0.28	0.29	0.30	0.32	0.39	0.11
						[21.06]

Table 4: Emotion beta portfolio average excess returns and alphas.

The table presents portfolio average excess returns across different return adjustment models and unconditional factor model alphas. For each month, we form quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. In Panel A, Column two presents the value-weighted average excess returns. Column three reports the average value-weighted excess returns after adjusting for characteristics adjusted return of Daniel, Grinblatt, Titman, and Wermers (1997, DGTW). Column four adjusts for market returns in generating portfolio value-weighted excess returns. Column five presents the value-weighted average excess returns after adjusting for Fama-French (1997) 48-industry returns. The last row presents the differences between high and low β^{MEI} quintiles. Panel B presents emotion beta-based portfolio alphas. Columns two and three report the alphas (α_5 and α_7) for equal-weighted portfolios. Columns four and five report the same for value-weighted portfolios. α_5 is the alpha relative to the market, size, value, profitability, and investment factors; α_7 is the alpha relative to the market, size, value, momentum, profitability, investment, and liquidity factors. The last row presents the differences between high and low quintiles. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Portfolio average excess returns across return adjustment models.

Portfolios	RET-RF	DGTW return	Market-adjusted return	Industry-adjusted return
Low	1.06	0.27	0.44	0.26
2	0.96	0.22	0.34	0.21
3	0.98	0.23	0.36	0.22
4	1.15	0.31	0.53	0.43
High	1.60	0.81	0.98	0.81
High-Low	0.54	0.54	0.54	0.55
	[2.43]	[3.80]	[2.42]	[3.19]

Panel B: Portfolio alphas using unconditional factor models.

	Equal-weighted		Value-weighted	
Portfolios	α_5	α_7	α_5	α_7
Low	0.15	0.17	0.42	0.44
2	0.08	0.10	0.24	0.24
3	0.13	0.17	0.31	0.33
4	0.22	0.26	0.38	0.35
High	0.56	0.59	0.91	0.90
High-Low	0.41	0.42	0.49	0.46
	[5.23]	[5.15]	[2.74]	[2.59]

Table 5: Persistence of 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}), log 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). The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

n-year-ahead β^{MEI}	$n = 1$	$n = 2$	$n = 3$	$n = 4$	$n = 5$
Univariate predictive regressions	0.27	0.20	0.13	0.10	0.07
	[14.36]	[10.95]	[9.31]	[9.57]	[7.06]
Controlling for lagged variables	0.34	0.22	0.13	0.07	0.02
	[15.13]	[12.83]	[7.11]	[8.23]	[2.29]

Table 6: Fama-MacBeth regressions with 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, tone, and uncertainty 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 a 60-month rolling regression of excess returns on market emotion index and Fama-French three-factors—market, size, and value. Then, we take the absolute value of β^{MEI}. The mood beta (β^{Mood}) (see, Hirsheifer, Jian, DiGiovanni, 2020) is computed by running a 10-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 a 60-month rolling regression of excess returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. By estimating a 60-month rolling regression of excess returns on University of Michigan's consumer confidence index and Fama-French three-factors, we generate the consumer confidence beta (β^{UMCCI}). By estimating a 60-month rolling regression of excess returns on LM and Henry tone and Fama-French three-factors, we generate the tone betas (β^{LM} and β^{Henry}). The tones are derived by taking the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and MacDonald (2011) and Henry's (2008) positive and negative dictionaries. The uncertainty beta (β^{UNC}) is computed by running a 60-month rolling regression of excess returns on Jurado et al.'s (2015) economic uncertainty index, MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. By estimating a 60-month rolling regression of excess returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index and Fama-French three-factors, we generate the economic policy uncertainty beta (β^{EPU}). For brevity, we do not report intercepts and coefficients of lagged control variables. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
β^{MEI}	0.46	0.46	0.49	0.43	0.42	0.46	0.45	0.44	0.35
	[2.29]	[3.65]	[3.91]	[3.36]	[3.38]	[3.72]	[3.75]	[3.55]	[1.97]
β^{Mood}	-0.10								-0.13
	[-0.36]								[-0.47]
β^{SENT}		0.79						0.47	1.17
		[0.98]						[0.56]	[0.79]
β^{UMCCI}			-3.49					-1.53	-2.33
			[-0.26]					[-0.72]	[-0.62]
β^{UNC}				-0.08				-0.15	-0.25
				[-1.23]				[-2.06]	[-1.89]
β^{EPU}					-0.15			0.49	0.27
					[-0.33]			[1.19]	[0.37]
β^{LM}						0.21		0.35	0.47
						[1.19]		[1.48]	[1.02]
β^{Henry}							0.15	0.20	0.09
							[0.58]	[0.60]	[0.20]
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	10.6874%	9.105%	9.105%	9.105%	9.0511%	9.0712%	9.0914%	9.6311.07%	11.639%
N months	137	287	287	287	287	287	287	287	137

Table 7: Fama-MacBeth regression in high and low mood period.

The table reports the time-series averages of the slope coefficients during high and low mood period obtained from regressing monthly excess stock returns (in percentage) on previous months emotion, mood, sentiment, tone, and uncertainty betas and a set of lagged control variables (used in Table 2) using Fama-MacBeth methodology. We determine high and low mood periods following Hirshleifer Jian, DiGiovanni (2020). 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 two and bottom two months ranked based on the equal-weighted CRSP excess returns realized in a given year. The emotion beta (β^{MEI}) is derived from running a 60-month rolling regression of excess returns on market emotion index and Fama-French three-factors—market, size, and value. The mood beta (β^{Mood}) (see Hirsheifer et al., 2020) is computed by running a 10-year rolling regression of excess stock returns on equal-weighted CRSP excess returns during prespecified and realized high and low mood months. The sentiment beta (β^{SENT}) is computed by running a 60-month rolling regression of excess returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. By estimating a 60-month rolling regression of excess returns on University of Michigan's consumer confidence index and Fama-French three-factors, we generate the consumer confidence beta (β^{UMCCI}). By estimating a 60-month rolling regression of excess returns on LM and Henry tone and Fama-French three-factors, we generate the tone betas (β^{LM} and β^{Henry}). The tones are derived by taking the ratio of difference between positive and negative word counts to the total of positive and negative word counts as suggested by Loughran and MacDonald (2011) and Henry (2008). The uncertainty beta (β^{UNC}) is computed by running a 60-month rolling regression of excess returns on Jurado et al.'s (2015) economic uncertainty index, MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. By estimating a 60-month rolling regression of excess returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index and Fama-French three-factors, we generate the economic policy uncertainty beta (β^{EPU}). For brevity, we do not report intercepts and coefficients of lagged control variables. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

	High mood period	Low mood period
β^{MEI}	2.15	1.09
	[6.09]	[2.94]
β^{Mood}	0.62	-1.14
	[2.81]	[-3.50]
β^{SENT}	-1.17	-0.75
	[-1.08]	[-0.67]
β^{UMCCI}	-0.74	-2.51
	[-0.35]	[-1.12]
β^{UNC}	-1.01	-1.31
	[-1.79]	[-2.53]
β^{EPU}	-5.86	-5.21
	[-1.69]	[-1.60]
β^{LM}	-2.66	-4.97
	[-1.18]	[-1.54]
β^{Henry}	6.82	4.49
	[2.01]	[1.20]
Firm controls & risk factors	Yes	Yes
Industry Effects	Yes	Yes
Adj. R-Squared	20.22%	23.55%
N months	107	50

Table 8: Equity portfolios as test assets.

At the end of each month, we independently sort all stocks into two groups based on market capitalization (size) using the median CRSP size breakpoint and three emotion beta (β^{MEI}) groups using the CRSP 20th and 80th percentile values of β^{MEI}. The intersections of the two size groups and the three β^{MEI} groups generate six portfolios. The value-weighted return (the first row) of the emotion beta factor is taken to be the average return of the two value-weighted high-β^{MEI} portfolios minus the average return of the two value-weighted low-β^{MEI} portfolios. The equal-weighted return (the second row) of the emotion beta factor is measured by the average return of the two equal-weighted high-β^{MEI} portfolios minus the average return of the two equal-weighted low-β^{MEI} portfolios. The table reports the average monthly returns of the emotion beta factor and the alphas (α_5^1, α_5^2, α_4, and α_7). α_5^1 is the alpha relative to the market, size, book-to-market, momentum, and liquidity factors; α_5^2 is the alpha relative to the market, size, book-to-market, investment, and profitability factors; α_4 is the alpha relative to the market, size, investment, and profitability factors; and α_7 is the alpha relative to the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is January 1995 to December 2018.

	Average return	α_5^1	α_5^2	α_7	α_4
VW β^{MEI} factor	0.44	0.30	0.61	0.61	0.66
	[2.62]	[2.94]	[4.10]	[4.13]	[3.38]
EW β^{MEI} factor	0.81	0.70	1.01	0.99	1.05
	[4.92]	[6.60]	[7.12]	[7.14]	[5.67]

Table 9: Univariate portfolios of stocks sorted by alternative measures of emotion beta.

For each month, we sort stocks into quintile portfolios based on emotion beta (β^{MEI}), estimated using alternative models:

Model 1: $R^e_{t+1} = \alpha_{i,t} + \beta^{MEI^a}_{i,t}.MEI_t + \beta^{MKT}_{i,t}.MKT_t + \varepsilon_{i,t},$

Model 2: $R^e_{t+1} = \alpha_{i,t} + \beta^{MEI^b}_{i,t}.MEI_t + \beta^{MKT}_{i,t}.MKT_t + \beta^{SMB}_{i,t}.SMB_t + \beta^{HML}_{i,t}.HML_t + \beta^{MOM}_{i,t}.MOM_t + \varepsilon_{i,t},$

Model 3: $R^e_{t+1} = \alpha_{i,t} + \beta^{MEI^c}_{i,t}.MEI_t + \beta^{MKT}_{i,t}.MKT_t + \beta^{SMB}_{i,t}.SMB_t + \beta^{HML}_{i,t}.HML_t + \beta^{MOM}_{i,t}.MOM_t$
$+\beta^{IVA}_{i,t}.IVA_t + \beta^{ROE}_{i,t}.ROE_t + \beta^{LIQ}_{i,t}.LIQ_t + \varepsilon_{i,t},$

Model 1 controls for the market (MKT) factor. Model 2 controls for the market (MKT), size (SMB), value (HML), and momentum (MOM) factors. Finally, Model 3, controls for the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors. The columns two and three report the alphas (α_5 and α_7) for equal-weighted portfolios. The columns four and five report the same for value-weighted portfolios. α_5 is the alpha relative to market, size, value, profitability, and investment factors; and α_7 is the alpha relative to the market, size, value, momentum, profitability, investment, and liquidity factors. The last row in each panel presents the alpha differences between high and low quintiles. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Portfolios sorted on β^{MEI} using Model 1.

	Equal-weighted		Value-weighted	
Portfolios	α_5	α_7	α_5	α_7
Low	0.16	0.19	0.33	0.34
2	0.12	0.14	0.44	0.44
3	0.18	0.21	0.26	0.28
4	0.28	0.31	0.41	0.39
High	1.38	1.43	0.70	0.66
High – Low	0.43	0.42	0.37	0.32
	[5.53]	[5.39]	[2.31]	[2.06]

Panel B: Portfolios sorted on β^{MEI} using Model 2.

	Equal-weighted		Value-weighted	
Portfolios	α_5	α_7	α_5	α_7
Low	0.18	0.20	0.40	0.42
2	0.13	0.15	0.27	0.27
3	0.16	0.19	0.37	0.38
4	0.24	0.29	0.26	0.23
High	0.62	0.63	1.02	1.01
High – Low	0.44	0.43	0.62	0.59
	[5.56]	[5.52]	[3.68]	[3.56]

Panel C: Portfolios sorted on β^{MEI} using Model 3.

	Equal-weighted		Value-weighted	
Portfolios	α_5	α_7	α_5	α_7
Low	0.15	0.17	0.33	0.34
2	0.12	0.16	0.33	0.35
3	0.16	0.18	0.30	0.30
4	0.25	0.29	0.41	0.38
High	0.65	0.68	0.86	0.88
High – Low	0.50	0.51	0.53	0.54
	[6.22]	[6.14]	[3.51]	[3.61]

Table 10: Univariate portfolio alphas – Robustness tests.

The table reports emotion premium across different subsample of stocks, alternatives measures to generate market emotion index (MEI), and emotion valency-based approaches. In Panel A, we adjust for microcaps and for stocks included in the S&P 500 index, largest 1000, and based on Amihud's illiquidity measure most liquid 1000 stocks. For each month, we form quintile portfolios by sorting the subsampled stocks based on their emotion beta (β^{MEI}), where quintile 1(5) contains stocks with the lowest (highest) β^{MEI} during the previous month. For microcaps, we use the definition of Ball et al. (2020) and consider all but microcap stocks with market values of equity above the *20th* percentile of the market capitalization. The columns report alphas (α_7) for value-weighted portfolios. The α_7 is the alpha relative to the market, size, value, momentum, profitability, investment, and liquidity factors. Panel A also presents emotion premium (α_7) for S&P 500, large, and liquid stocks. Panel B reports emotion premium (α_7) generated using alternative market emotion indices. First, we standardize MEI. Second, we use a time weight where MEI at day *d* receives more weight than MEI of day *d-1*. Thus, we compute the monthly MEI by weighting daily MEI by their respective time-weights (*Time-weighted* $MEI_t = \sum_{d=1}^{t} MEI_d \times weight_d$). Third, '*Total MEI*' is calculated as the ratio of sum of excitement and anxiety words to total words in a month ($Total\ MEI_t = \frac{Excitement_t + Anxiety_t}{Total\ Words_t}$). Fourth, '*Net MEI*' is calculated as the ratio of the difference between excitement and anxiety words to total words in a month ($Net\ MEI_t = \frac{Excitement_t - Anxiety_t}{Total\ Words_t}$). In Panel C, we sort portfolios based on above and below median of rolling asymmetric emotion beta (β^{MEI}). we also report alpha (α_7) estimates for portfolios sorted on excitement beta and anxiety beta. To generate excitement and anxiety beta we estimate eq. (5) using excitement and anxiety separately. The last row in each panel presents the differences between high and low quintiles. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Emotion premium across different stock subsamples.

Portfolios	Microcaps adjusted	S&P 500	Largest 1000	Liquid 1000
Low	0.46	0.45	0.46	0.51
2	0.18	0.23	0.25	0.22
3	0.41	0.33	0.33	0.34
4	0.27	0.38	0.23	0.24
High	0.84	0.93	0.88	0.9
High – Low	0.38	0.48	0.42	0.39
	[2.39]	[2.75]	[2.70]	[2.41]

Panel B: Alternative market emotion index (MEI) based emotion premium.

Portfolios	Standardized MEI	Time weighted MEI	Total MEI	Net MEI
Low	0.35	0.44	0.23	0.31
2	0.3	0.29	0.34	0.37
3	0.42	0.28	0.35	0.36
4	0.24	0.34	0.42	0.43
High	0.98	0.99	1.09	0.89
High – Low	0.63	0.55	0.86	0.58
	[3.68]	[3.38]	[4.11]	[3.24]

Panel C: Emotional valency-based emotion premium.

<table>
<tr><th></th><th colspan="2">Asymmetric β^{MEI}</th><th colspan="2">Emotions</th></tr>
<tr><th>Portfolios</th><th>Above median</th><th>Below median</th><th>Excitement</th><th>Anxiety</th></tr>
<tr><td>Low</td><td>0.42</td><td>0.42</td><td>0.35</td><td>0.31</td></tr>
<tr><td>2</td><td>0.36</td><td>0.22</td><td>0.29</td><td>0.29</td></tr>
<tr><td>3</td><td>0.35</td><td>0.17</td><td>0.25</td><td>0.34</td></tr>
<tr><td>4</td><td>0.66</td><td>0.29</td><td>0.45</td><td>0.48</td></tr>
<tr><td>High</td><td>0.98</td><td>0.87</td><td>1.05</td><td>0.95</td></tr>
<tr><td>High – Low</td><td>0.56</td><td>0.45</td><td>0.70</td><td>0.64</td></tr>
<tr><td></td><td>[2.43]</td><td>[2.17]</td><td>[3.85]</td><td>[3.73]</td></tr>
</table>

Appendix 1

Table A1: Summary statistics for the newspaper dataset.

The table reports on the availability and total number of articles collected from each newspaper. All newspaper articles except for 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 these needs 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 December 2018.

# Newspapers	Availability	Articles	Percentage of total
(1) Atlanta Journal and Constitution	1991-2018	2,406	4.03
(2) The Augusta Chronicle	1993-2018	2,018	3.38
(3) The Austin American-Statesman	1995-2018	1,338	2.24
(4) Daily News (New York)	1995-2018	817	1.37
(5) Dayton Daily News	1994-2018	1,754	2.94
(6) The New York Post	1997-2018	2,706	4.54
(7) The New York Times	1990-2018	9,980	16.73
(8) The Palm Beach Post	2011-2018	150	0.25
(9) The Philadelphia Inquirer	1994-2018	2,887	4.84
(10) Pittsburgh Post-Gazette	1990-2018	5,417	9.08
(11) Richmond Times Dispatch	1996-2018	377	0.63
(12) S&P Daily News	1990-2018	1,629	2.73
(13) The Salt Lake Tribune	1995-2018	1,141	1.91
(14) The Santa Fe New Mexican	1995-2008	82	0.14
(15) St. Louis Post Dispatch	1990-2018	3,907	6.55
(16) Star Tribune (Minneapolis)	1991-2018	643	1.08
(17) Tulsa World	1995-2018	4,312	7.23
(18) The USA Today	1990-2018	7,046	11.81
(19) Wall Street Journal	1990-2018	3,715	6.23
(20) The Washington Post	1990-2018	6,971	11.68
(21) Wisconsin State Journal	1995-2018	369	0.62
Total articles		59,665	
Total of NYT, WP, USAT, WSJ		27,712	46.44

Table A2: Conditional factor models.

The table presents portfolio alphas based on conditional factor models. For each month, we form quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. Panel A and Panel B present both equal- and value-weighted portfolio alpha estimates 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) that follows up and down phases of the dot.com bubble and great financial crisis by following Taffler et al. (2021); (iii) the *cay* residual of Lettau and Ludvigson (2001); (iv) the paper bill spread; (v) the term spread; and (vi) the default spread. Each individual column controls for Fama-French factors (MKT, SMB, HML, MOM, RMW, CMA), LIQ factor, and their interaction with each U.S. systematic risk factors. The last two columns in each panel include interaction with all the time varying U.S. systematic risk factors with Fama-French and LIQ factors at the same time. The last two rows in each panel present the differences between high and low quintiles. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Equal-weighted

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	0.16	0.10	0.11	0.13	0.12	0.12	0.12	0.11
2	0.07	0.03	0.03	0.07	0.05	0.07	0.04	0.04
3	0.13	0.07	0.09	0.13	0.12	0.12	0.11	0.09
4	0.24	0.19	0.17	0.22	0.21	0.21	0.23	0.21
High	0.42	0.42	0.38	0.43	0.42	0.41	0.36	0.37
High-Low	0.26	0.32	0.27	0.30	0.30	0.29	0.24	0.26
	[2.88]	[3.87]	[3.25]	[3.82]	[3.78]	[3.29]	[2.84]	[3.10]

Panel B: Value-weighted

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	0.46	0.44	0.45	0.44	0.44	0.46	0.40	0.42
2	0.26	0.25	0.26	0.26	0.25	0.27	0.21	0.23
3	0.34	0.34	0.35	0.37	0.38	0.34	0.37	0.35
4	0.29	0.35	0.30	0.30	0.32	0.31	0.36	0.32
High	0.87	0.99	0.90	0.92	0.90	0.92	0.98	0.92
High-Low	0.41	0.55	0.45	0.48	0.46	0.46	0.58	0.50
	[2.09]	[3.16]	[2.35]	[2.68]	[2.65]	[2.40]	[2.93]	[2.65]

Table A3: Average emotion beta across size and book-to-market.

The table shows average emotion beta (β^{MEI}) across size and book-to-market quintiles. First, stocks are sorted based on size into quintile portfolios and then, each of the size quintiles are sorted again on book-to-market. After bivariate sorting, the table reports average emotion beta across quintiles. The estimation period is from January 1995 to December 2018.

		Size				
	Portfolios	Small	2	3	4	Big
	Low	0.67	0.46	0.49	0.24	0.15
	2	0.38	0.30	0.24	0.19	0.14
Book-to-market	3	0.29	0.25	0.22	0.17	0.14
	4	0.26	0.23	0.20	0.17	0.14
	High	0.25	0.21	0.18	0.16	0.13

Table A4: Bivariate sorts.

In this table, stocks are first sorted into quintiles based on a firm characteristic, and then within each characteristic quintile are further sorted into quintiles based on emotion beta (β^{MEI}). We report both equal- and 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. For each emotion beta quintile, we average alphas across the five characteristic groups. The firm characteristics are size (market capitalization), book-to-market (B/M), gross profitability (GP), and annual growth of book assets (I/A). The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in square brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Equal-weighted				
Portfolios	Size	B/M	GP	I/A
Low	0.09	0.09	0.10	0.10
2	0.06	0.07	0.08	0.10
3	0.08	0.02	0.04	0.04
4	0.15	0.14	0.11	0.12
High	0.52	0.31	0.30	0.31
High-Low	0.43	0.22	0.20	0.21
	[4.82]	[2.40]	[2.27]	[2.50]
Panel B: Value-weighted				
Portfolios	Size	B/M	GP	I/A
Low	0.31	0.38	0.44	0.35
2	0.38	0.25	0.27	0.36
3	0.28	0.28	0.23	0.23
4	0.29	0.27	0.30	0.32
High	0.66	0.91	0.89	0.73
High-Low	0.35	0.53	0.45	0.38
	[2.16]	[2.61]	[2.39]	[2.12]

Table A5: Top ten emotional and tonal words.

The table presents top ten emotional and tonal words. Emotional words (Taffler et al., 2021) includes excitement and anxiety. Tone includes Loughran and McDonald (2011), positive and negative words. The words are counted from twenty-one newspaper articles (see Table A2 for the list of newspapers) from January 1990 to December 2018.

Word	Excitement	Mentions	Anxiety	Mentions	Positive	Mentions	Negative	Mentions
1	Rise	148,897	Fall	35,431	Gain	88,540	Decline	50,036
2	Jump	19,408	Worry	17,432	Good	31,419	Loss	34,472
3	Climb	18,175	Risk	16,687	Strong	24,395	Cut	30,136
4	Confident	13,775	Fear	15,942	Better	21,422	Lost	23,606
5	Boost	12,728	Bear Market	13,896	Best	19,031	Concern	21,547
6	Bull Market	11,727	Volatile	12,955	Confident	13,775	Fear	15,942
7	Surprise	8,844	Tumble	8,778	Boost	12,728	Slow	15,695
8	Speculate	5,592	Pressure	7,005	Improve	12,666	Severe	13,301
9	Optimism	5,315	Uncertainty	5,684	Benefit	10,806	Volatile	12,955
10	Expand	5,028	Struggle	4,734	Rebound	10,233	Bad	11,903

Table A6: Proportion of articles across emotion and tone scores.

The table reports the percentage of articles across quintiles of market emotion index and tonal scores over the sample period. The market emotion index is the ratio of difference between excitement and anxiety word counts to the total of excitement and anxiety word counts. The tone is the ratio of difference between positive and negative word counts to the total of positive and negative word counts. The sample period is from 1990 to 2018.

			Market Emotion Index				
	Quintiles		1	2	3	4	5
		Scores	0.00	0.11	0.29	0.50	1.00
	1	-0.70	**0.096**	0.014	0.026	0.028	0.038
	2	-0.47	0.077	**0.022**	0.040	0.036	0.028
Tone	3	-0.25	0.056	0.021	**0.048**	0.041	0.032
	4	0.00	0.052	0.020	0.051	**0.050**	0.042
	5	1.00	0.030	0.013	0.039	0.051	**0.049**

Appendix 2

Case study 1

The New York Times
February 28, 2012 Tuesday
Late Edition – Final

S.&P. 500 closes at highest point since mid-2008

The Standard & Poor's 500-stock index closed at its highest level since mid-2008 on Monday, extending gains for a third session as oil prices retreated after a recent rally and data showed further improvement in the nation's housing market.

The S.& P. and the NASDAQ both posted small gains, while the Dow closed barely lower. An industry group reported that contracts for home resales hit the highest level in nearly two years in January, lifting the Dow Jones home construction index 1.5 percent.

A decline of about 1 percent in the price of oil relieved concerns that high energy prices could hurt the still-fragile economic recovery. Brent crude ended at $124.17, down $1.30. "Anything above $120 to $130 is clearly the level at which the global economy is going to have a hard time growing at a pace that is consistent with a very robust rate of growth," said Natalie Trunow, chief investment officer of equities at Calvert Investment Management in Bethesda, Md.

The Standard & Poor's 500-stock index was up 1.85 points, or 0.14 percent, at 1,367.59. It has rallied 9 percent since the start of the year, and it rose as high as 1,371.94 on Monday before paring gains. Though the S.& P. 500 closed below the day's high, it was still its highest finish since June 2008.

The Dow Jones industrial average was down 1.44 points, or 0.01 percent, at 12,981.51. The NASDAQ composite index was up 2.41 points, or 0.08 percent, at 2,966.16. The Dow industrials topped 13,000 several times during the day but failed, for the third time in the last five sessions, to close above that level.

Oil's recent rally has been driven by worries over disruptions to Middle East supplies resulting from sanctions against Iran. Energy companies fell with oil prices. Shares of Exxon Mobil ended down 0.1 percent at $87.23.

The fourth-quarter earnings period is in the final stretch. As of Monday, 468 S.& P. 500 companies had reported results, with 63 percent beating analysts' expectations. On Monday, Lowe's, the home improvement chain, reported higher-than-expected quarterly sales, and its shares rose 18 cents, or 0.7 percent, to $27.34.

Biotech stocks fell after Dendreon said demand was soft for its high-priced Provenge prostate cancer treatment as the year began, and forecast slow sales growth in the first quarter. Dendreon slumped $3.05, or 20.5 percent, to $11.81. The N.Y.S.E. Arca biotech index lost 1.5 percent.

Interest rates were lower. The Treasury's benchmark 10-year note rose 15/32, to 100 22/32, and the yield fell to 1.93 percent from 1.98 percent late Friday.

Score: MEI 0.50 and LM 0.00

Case study 2

Wall Street Journal
October 06, 2007 Saturday
Eastern edition; New York, N.Y.

How safe is the soaring stock market?; Rise is driven by view of where safety lies, but some see dangers

Full text: Investors who just weeks ago were fleeing stocks now think it's safe to return – driving the markets to a record high in the past week. Their hope: that the worst is over. Much of the buying is driven by the notion that stocks are a safer bet than risky debt and other investments at the heart of the summer's market meltdown. But there are some who question whether the market is being complacent.

"This story is not over," says Steven Romick, manager of the $1.4 billion FPA Crescent Fund. "There are a lot of risks in the market."

Among them: For the first time since the 2001 terrorist attacks, corporate profits are expected to post a third-quarter decline. The companies in the Standard & Poor's 500-stock index are now expected to see a 0.4% drop in operating earnings, a figure that doesn't yet reflect the sizable hits announced on Friday by Merrill Lynch & Co., Washington Mutual Inc. and Alcoa Inc. All three are in the S&P 500.

Merrill Lynch on Friday said it would take a $5.5 billion hit because of losses in complex bonds stemming from this summer's market meltdown. Washington Mutual, meanwhile, warned that net income will fall 75% in the third quarter because of problem loans. Looking at earnings forecasts, S&P analyst Howard Silverblatt says, "Is there light at the end of the tunnel, or is it an oncoming train?"

Soaring stock prices suggest that investors see a strong rebound in earnings, and Wall Street analysts share that view, predicting that corporate profits will only shrink for one quarter before rebounding strong in the fourth quarter and holding that momentum through next year. Friday's stock gains were fueled by an unexpectedly strong employment report, suggesting that the economy has enough strength to avoid recession. The Dow Jones Industrial Average gained 91.70 points, or 0.7%, up 9.5% from its mid-August low. The S&P 500 index closed at a record high. Even stocks that announced problem earnings jumped. Merrill Lynch gained 2.5% and Washington Mutual rose 2.2%.

In fact, says, Fritz Meyer, senior market strategist at AIM Investments, many are betting that even the third quarter won't turn out to be as bad as feared. "My hunch – and maybe what the market is hunching – is that we're going to get an upward surprise to third- quarter earnings." He notes that during the first half of the year, many companies posted better-than-expected profits. "The pattern has been too persistent not to think that."

Investors are banking on a solid earnings rebound in the fourth quarter, in large part based on the assumption that the economy will continue to grow, albeit at a slower pace. Earnings on S&P 500 companies are expected to grow by 10.5% in the final three months of the year, according to S&P's data. Particular strength is anticipated in health care, technology and telecommunications companies. "We're not seeing the recession scenarios in earnings expectations," says Thomas Loeb, chairman of Mellon Capital Management, which manages $240 billion.

FPA's Mr. Romick argues, however, that there is a big risk in underestimating the impact that the housing-market collapse will have on consumers. That could in turn bleed over to non-U.S. economies that still rely heavily on demand from America's buyers – and are expected to be an important prop to corporate earnings.

"This is the first time in 70 years or so where home prices have declined nominally," he notes, at the same time that Americans have been borrowing against their houses, in effect using them as "ATM machines." The impact on the consumer behavior may not yet be fully felt, he says.

Still, some investors argue that stocks are the best option among a lackluster crowd of options. AIM's Mr. Meyer says U.S. stocks look good from a valuation standpoint.

The S&P 500 is trading at 14.6 times 2008's expected earnings, a ratio that while not as attractive as a few weeks ago, is "still cheap." Indeed, the bond market isn't presenting much of an attractive alternative. Unless there is a substantial worsening of the economy, the prospect for substantially lower interest rates – which would trigger a rally in bond prices, since interest rates and bond prices move in opposite directions – doesn't appear to be in the cards.

And while the additional yield offered by corporate bonds or other non-U.S. Treasury offerings is higher than earlier in the year, that difference is still historically low except in the most battered and trickiest corners of the bond market. "We find equities very attractive to the alternatives," says Mellon's Mr. Loeb. In Mr. Loeb's portfolios, such as the $11.5 billion Vanguard Asset Allocation fund, which he co-manages, 80% of assets are in stocks. "It's an aggressive" posture, he says.

Even if stocks seem attractive to other investments, holding them requires a stronger stomach today than a year ago. Between July 19 and late September, roughly half the trading sessions featured swings in the S&P 500 of at least 1%. By contrast, in all of 2005 and 2006 combined there were less than 60 trading days trading days in which prices moved more than 1%.

Score: MEI -0.40 and LM 0.02