# Investor Emotions and Asset Prices

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*26 February 2022*

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**JEL classification:** G12, G14.

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This study examines the impact of integral emotions on portfolio decisions and asset prices. Using a new dictionary of emotion keywords, we measure the emotional state of the market and compute firm-level sensitivity to changes in market-level emotions (i.e., emotion beta). We find that stocks with high emotion betas outperform low emotion beta firms and this performance differential is corrected in about ten months. During the 1990-2018 sample period, a Long-Short investment strategy with high-emotion beta stocks in the Long portfolio and low-emotion beta stocks in the Short portfolio generates an alpha ranging from 6.36% to 7.44%. This evidence of emotion-based predictability is distinct from the known pricing effects of mood, sentiment, economic and policy uncertainty, and tone. Collectively, our findings show that emotional connections between investors and firms are priced.

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## 1. Introduction

Stock market participation meets both the emotional and financial needs of investors. Investors are likely to enter into emotional relationships with stocks, which could affect their perceptions of risk and return. Since financial markets are difficult to predict, 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 which may both be emotionally charged.

A wide range of powerful investor emotions can collapse into two broad emotional states such as 'excitement' and 'anxiety' reflecting the emotional states of the brain (Kuhnen and Knutson, 2011). These emotions could modify investors' risk perceptions, or beliefs, or both. Even sophisticated investors' investment decisions can be affected by their emotions (Kuhnen and Knutson, 2011; Tuckett and Taffler, 2012), although they do not acknowledge this directly (Taffler, Spence, and Eshraghi, 2017).

The role of emotions in decision-making is a dominant theme in the psychology literature.[1] Financial economists have also recognized the importance of *incidental* emotions such as weather, sentiment, and mood in investment decisions and financial market outcomes (e.g., Hirshleifer and Shumway, 2003; Edmans, Garcia, and Norli, 2007; Hirshleifer, Jiang, and DiGiovanni, 2020; Obaid and Pukthuanthong, 2021; Edmans et al., 2021).[2] In contrast, the potential impact of *integral* or fundamental emotions (e.g., excitement, anxiety, fear, panic, anger, guilt, etc.) on financial decisions and aggregate market outcomes has received relatively less attention in the existing finance literature.

In this paper, we propose a new method for capturing the potential emotional relationships between investors and firms. Drawing on the object relations theory and emotions

[1] Consistent with the psychology literature, we use the terms 'emotion', 'affect', and 'feeling' interchangeably to convey subjective experience (Auchincloss and Samberg, 2012).

[2] *Incidental* emotions are induced by exogenous factors that are unrelated to the current decision (e.g., weather), while *integral* emotions are endogenous as they are generated by considerations of the current decision task itself (e.g., excitement (or anxiety generated by the possibility of a large gain (or loss) in the future). The experience of investing in a certain firm can generate additional utility beyond the utility from wealth.

in the decision-making literature, we measure the time-varying emotional utility of stocks for investors in terms of the feelings of excitement and anxiety that they generate. We estimate each stock's emotional utility (EU) to investors, and examine whether this firm-level measure of sensitivity to changes in market-level emotional state (i.e., emotion beta) can explain cross-sectional patterns in stock returns.

The motivation for our study comes from the important role of emotions in the decision-making literature (e.g., Lerner et al., 2015), and object relations theory in psychology. The object relations theory describes the ambivalent relations of attachment, attraction and repulsion (i.e., 'love' and 'hate') we establish in our minds with 'objects' based on our experiences of early emotional relationships (e.g., Tuckett and Taffler, 2012; Auchincloss and Samberg, 2012). It also highlights the internal representations of people, ideas, or things based on our emotional experiences. These connections are often beyond people's conscious awareness and may even be more powerful as a result.

In our empirical tests, we first construct a market-level emotion index to measure an individual stock's emotional utility to investors. We construct this index using a standard bag-of-words technique with keyword dictionaries made up of 134 excitement-related words and 161 anxiety-related words.[3] For each month during our January 1990 to December 2018 sample period, we use the total of excitement and anxiety word counts in newspaper articles to the total number of words in a month to derive our market emotion index. We *add* excitement and anxiety keywords, as Posner, Russell, and Petersen (2005) demonstrate, affective states are not independent but interconnected, and arise from common, overlapping

[3] These lexicons were originally constructed to analyze the emotional trajectory of an asset-pricing bubble by systematically analyzing synchronous media coverage using a keyword-in-context (KWIC) approach (Taffler, Agarwal, and Obring, 2021). This set of keywords exhibits out-of-sample validity when investigating the emotional trajectory of the U.S. stock market during the Global Financial Crisis. An alternative approach to capture emotions from narratives has been recently used to measure social networks (Tuckett, Smith, and Nyman, 2014) and changes in exuberance before major economic crisis (Nyman, Kapadia, and Tuckett, 2021)

neurophysiological systems. Also, affective states originating from a similar negative or positive valence can have completely opposite impact on decision making (see for example, Keltner, 2001). This makes the tracking of valence-based impact extremely difficult. Rather, we focus on the intensity or emotional 'arousal' investors feel which is more direct and affects their decision making directly (Loewenstein and Lerner, 2003). Our market emotion index is designed to capture the emotional engagement of investors with the overall stock market.

Our choice of using text to capture the emotional state of the market is based on the observation that news articles are likely to contribute to the emotional appeal of individual stocks for investors since much of the information investors use to make stock selection decisions is provided by the media. In particular, media coverage keeps individual stocks and the market alive in investors' minds, and in the spotlight of public discussion (e.g., Engelberg and Parsons, 2011; Engelberg, McLean, and Pontiff, 2018). Recognizing this, and how media reports reflect feelings about the state of the stock market dynamically (see, for example, Tetlock, 2007; Dougal et al., 2012; Shiller, 2019), we use national- and local-level newspaper articles to measure salient contemporaneous investor emotions, and use these to construct our aggregate market emotion index.

To capture cross-sectional variation in emotional utility across individual firms, we estimate individual firm-level stock emotion betas using 60-month rolling regressions of excess stock returns on the market emotion index. These betas are our proxy for the emotional connections between investors and firms. In particular, the returns of a firm with high emotion beta exhibit greater sensitivity to variation in the emotional state of the overall market.

In our asset pricing tests, we transform our monthly emotion betas into conditional emotion-sensitive betas by taking their absolute values. This choice is based on our conjecture that investors are likely to be driven by the intensity of the emotional arousal/charge rather than its valence.[4] Specifically, we posit that investors are more attracted to stocks with high emotion beta, which in turn could affect their pricing. The more powerful the investor 'arousal', the greater the propensity to invest and the higher the prices in the near future. Conversely, the weaker a firm's emotional utility to investors, the lower the appeal of the stock to investors, and the lower the stock price will be in the short-term.

To examine the relation between stock emotion betas and cross-sectional patterns in stock returns, we first sort stocks into decile portfolios based on previous month emotion beta, and measure the monthly returns of the resulting portfolios. We find that the high emotion beta portfolio outperforms the low emotion beta portfolio. During the January 1995 - December 2018 sample period, the high-minus-low portfolio earns value-weighted abnormal returns ranging from 0.53% to 0.62% per month (*t*-statistic = 4.34 and 4.79, respectively) on a risk-adjusted basis. Similarly, the value-weighted average excess return is 0.55% per month (*t*-statistic = 2.51). This emotion beta-based trading strategy generates qualitatively similar alphas even when we adjust for risk using factor models with time-varying betas.

The economic significance of the alpha estimates persists for up to 10 months and then becomes insignificant. These results indicate that the alpha estimates of emotion beta portfolios capture the mispricing of stocks with high emotional sensitivity, and this eventually becomes corrected over the next year.

In additional tests, we estimate monthly Fama and MacBeth (1973) regressions and find that emotion beta is economically significant. It has a coefficient estimate of 0.69 with *t*-statistic of 2.73. In economic terms, this estimate implies that a one standard deviation shift in conditional emotion beta is associated with a $0.69 \times 1.278 = 0.88\%$ shift in stock return in the

[4] For example, when the stock price drops by a large amount, both contrarian and value-minded investors can become excited about the prospects of high returns from those investments in the future. And when the stock price increases by a large amount, momentum or trend-chasing investors may find its future prospects very attractive. In both instances, excess buying pressure could generate higher returns in the near future.

following month. Consistent with the factor model estimate, we find that the predictive ability of emotion beta remains strong for up to several months ahead.

We conduct several additional tests to examine the robustness of our core findings. First, following Baker and Wurgler (2006), we orthogonalize our market emotion index and construct three orthogonalized indices. To orthogonalize our base index, we collect residuals from regressions of MEI on (i) macroeconomy-related indicators (growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions); (ii) macro uncertainty and tone measures (VIX, economic uncertainty index (Jurado, Ludvigson, and, Ng, 2015, UNC), economic policy uncertainty index (Baker, Bloom, and Davis, 2016, EPU), investor sentiment (Baker and Wurgler, 2006, BWSENT), University of Michigan's Consumer Confidence Index, and two positive-/negative-based tone measures (Loughran and McDonald, 2011, LN; Henry, 2008, HN); and (iii) including both the measures listed in (i) and (ii). In all cases, we find strong support in favor of our main findings. Second, we measure emotion beta using alternative specifications and different variations in factor models, and show that it remains a significant predictor of future stock returns. In each case, the high-minus-low trading strategy earns positive and significant abnormal returns.

Next, we investigate whether our integral emotion beta predictability is distinct from the known predictive ability of incidental emotions such as seasonal mood (e.g., Hirshleifer 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 et al.'s (2016) economic policy uncertainty index (EPU) and Bali, Brown, and Tang's (2017) economic uncertainty index (UNC) betas. Using the Fama-MacBeth estimation framework, we find that the emotion beta still has a positive and significant coefficient estimate. This evidence indicates that the emotion beta effect is distinct from the other related determinants of future stock returns.

In additional robustness tests, we find our hedge portfolio produces a significant alpha even when we consider only the set of S&P 500 stocks, the largest 1000 stocks, or the 1000 most liquid stocks separately. We also find consistent results and significant alphas in different subperiods such as crisis and non-crisis, and high and low investor sentiment. In addition, our results are qualitatively similar across a range of emotion beta-based extreme portfolios. Overall, our findings from these robustness checks confirm that integral emotions are priced in the cross-section.

These findings are consistent with the observation that the emotional utility of stocks affects cross-sectional patterns in returns. Our study contributes to the investment psychology and decision-making literature, showing that fundamental emotions can drive investor behavior. Specifically, consistent with the affective circumplex model of emotions (e.g., Posner et al., 2005; Posner et al., 2009),[5] we find that it is the emotional intensity of investor engagement with a stock that is priced rather than simply its positive/negative valence.[6]

The intensity of the investor-firm emotional relation adds to conventional asset valuation criteria. In particular, investors' expectations of future gain, both as individuals and as a group, create excitement, but with the associated anxiety of future loss. We demonstrate that such an uncertainty-driven emotional process is an important driver of asset prices.

Second, our findings confirm those of experimental stock markets, which demonstrate that 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

[5] 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.

[6] Different emotions of the same valence influence judgments and choices in dissimilar ways (e.g., Lerner and Keltner, 2000; DeSteno et al., 2000). For example, even though fear and anger have the same negative valence, Lerner and Keltner (2001) document that fearful individuals make pessimistic judgements whereas angry individuals make optimistic judgements. In parallel, emotions with opposite valence such as anger and happiness can have a similar influence on judgements. Thus, we work with the intensity of the emotions investors experience rather than just emotional valency.

of excitement and anxiety and related emotions are likely to dominate due to the inherent unpredictability of future returns (Taffler et al., 2017). 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.

Our findings also 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. In particular, our study highlights the direct impact of fundamental investor emotions in the cross-section of stock returns in real-world markets. Our findings contribute to the growing finance literature that examines the relation between such incidental emotions as mood, sentiment, and weather by introducing the parallel impact of integral emotions on investor behavior.

More broadly, we identify a new return predictability mechanism and extend the return predictability literature (e.g., Cohen and Frazzini, 2008; Lou, 2014; Addoum and Kumar, 2016; Lee et al., 2019). In addition, our results supplement the news and finance literature by showing how news affects market prices through its impact on investor emotions.

One potential caveat with our findings is that the emotional states of investors cannot be directly captured. As such we have used an indirect, text-based approach to capture their emotional states of anxiety and excitement. Consequently, we cannot be certain that our results reflect the impact of investor emotions directly, and our results must be interpreted cautiously. A similar concern applies to other studies that examine the market impact of other factors such as investor mood and sentiment.

## 2. Related research and testable hypotheses

Recent studies in finance have focused on nonstandard investor preferences as captured by prospect theory, and incidental emotions such as weather, mood, and sentiment. In this study, our main objective 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. So far, study of the impact of emotions such as excitement and anxiety on investor judgments has been restricted to the laboratory.

The emotional meaning stocks have for investors has attractive properties for understanding their decision processes. 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 strongly affect cognitive processing (Loewenstein and Lerner, 2003).

Our emotion-driven return predictability hypothesis is motivated by the psychology of integral/fundamental emotions and object relations theory, and builds upon recent research that examines the relation 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). Cross-sectionally, Hirshleifer et al. (2020) find seasonal variation in mood can explain stock return seasonality.

The behavioral asset pricing literature also shows that investor sentiment can explain and predict stock returns, although investor sentiment itself is difficult to measure (Baker and Wurgler, 2006). Edmans et al. (2007) link soccer outcome-driven changes in investor sentiment with aggregate stock market return in the short-term, and most recently, Edmans et al. (2021) demonstrate that music sentiment impacts market returns and volatility consistent with sentiment induced temporary mispricing. Further, Obaid and Pukthuanthong (2021) demonstrate pessimism reflected by photographs in news items can predict market return reversals. Taken together, these studies indicate mood and sentiment can influence market valuation and stock returns.

Our paper extends this literature and focuses on feelings that are directly linked to investment decisions, i.e., integral or fundamental emotions. Integral emotions, as the emotion-imbued choice model of Lerner et al. (2015) illustrates, enter into the investor choice process that affects investment decisions. The effects of integral emotions are difficult to avoid (Rozin, Millman, and Nemeroff, 1986) and they are 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). Consequently, investors are likely to make sub-optimal decisions (see Kaufman, 1999; Hanoch, 2002).[7]

We introduce the concept of emotional utility and posit that investors enter into ambivalent emotionally-charged object relationships with the stocks they invest in of a 'love' and 'hate' nature and these affect their investment 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 conjecture investors are attracted to stocks with emotional 'glitter', i.e., high emotional utility. This we measure in terms of the emotions of excitement and anxiety they generate.

Once such an emotional bond exists, investors are likely to derive emotional utility from their investments, which may be reflected in the cross-section of stock returns. This observation generates our first testable hypothesis (H1): Emotion beta, which measures an asset's return sensitivity to the market emotion index, will be positively associated with future stock returns.

[7] In contrast, incidental emotions are less decision context specific (Watson and Tellegen, 1985), and tend to be short-lived.

We further conjecture that trend chasers and contrarian investors will both covet high emotion beta stocks as they expect to derive higher emotional utility from them. Trend chasers will buy more in up markets whereas contrarians will invest more in down markets. In both cases, investor demand will drive the price up, at least in the short-term. Thus, we 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 smaller growth stocks. Conversely, large value stocks are likely to have lower emotion utility, and thus be less attractive to investors. These observations are summarized in our second hypothesis (H2): The high emotion beta portfolio will outperform the low emotion beta portfolio.

Finally, we also examine whether the return predictability mechanism we identify relates to investor emotions or whether we are repackaging a known effect. If our predictability mechanism is novel, it should predict future stock returns even in the presence of established predictability measures such as mood, sentiment, and economic and policy uncertainty. This notion constitutes our third hypothesis (H3): Anxiety- and excitement-based return predictability is distinct from return predictability identified using mood, sentiment, and uncertainty measures.

## 3. Data and variable definitions

This section summarizes the main data sets and describes how we measure our key emotion beta variable and other stock-level variables.

### *3.1 Measuring and quantifying emotion*

It is difficult to measure and quantify emotion since it is not directly observed. The media helps generate and also reflects the emotions of its readers (Shiller, 2017). As such, newspaper articles are likely to be an ideal source to measure investor feelings about the stock market.

Unfortunately, newspapers do not regularly cover every firm listed on the three major main stock exchanges (NYSE, AMEX, and Nasdaq). Hillert, Jacobs, and Müller (2014) find the median number of articles published by the national media about a firm in a given year is only three. Most importantly, newspapers cover less than half of the U.S. stock market on the basis of at least one article about a firm per year. Such limited media coverage of many firms poses a barrier to constructing an appropriate dataset at the individual firm level directly.

Our innovation is to collect news items about the S&P 500 index, which newspapers cover extensively on a daily basis. We use these articles to construct a market-level emotion index, which we use subsequently to generate individual firm-level monthly stock betas.

We work with 59,665 news articles collected from 21 national and local level newspapers. Appendix Table A1 breaks down the number of articles by newspaper, and provides respective period coverage. The four widely-circulated national-level U.S. newspapers - The New York Times, The Washington Post, Wall Street Journal and USA Today - account for about half of our articles about the S&P 500 index.

These news articles are obtained 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%. 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 search keywords are present in the abstract, headline and main text. *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 is why we start the sample period in January 1990.

*3.2 Market emotion index*

Our goal is to quantify investor emotions at the firm-level. To construct such stock emotion betas, we first measure investors' emotional states from news articles about the stock market. To do this, we employ a standard dictionary-based textual analysis approach widely employed in the finance literature (e.g., Liu and McConnell, 2013; Garcia, 2013; Henry and Leone, 2016). Specifically, using the context-specific emotion keyword dictionaries of Taffler, Agarwal, and Obring (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.

Taffler et al. (2021) also demonstrate empirically a similar range of emotions are 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. We perform a principal component analysis (PCA) of the word counts of these seven emotion keyword lexicons and find these collapses into two factors. Excitement relates to the first factor, and anxiety mostly explains the second factor. As such, we work only with their excitement and anxiety keywords in this paper to simplify analysis.

Appendix C1 summarizes the lexicon construction method of Taffler et al. (2021) and Appendix C2 lists their excitement and anxiety keywords we employ in this paper.[8] We measure the relative strength of different emotions in any month in terms of the relative frequency of different categories of emotion keywords.

Kuhnen and Knutson (2011) draw on neuroscience to investigate investor risk-taking behavior and posit that the two affective states of excitement and anxiety influence risk

[8] 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.

preferences in the emotional brain. Motivated by their findings, we work with the emotions of excitement and anxiety in our asset pricing tests.

In experimental settings, Breaban and Noussair (2018) examine the relation between the emotions of excitement and fear/anxiety, and stock market activity, and Andrade et al. (2016) focus on the role of excitement in explaining stock market bubbles. Tuckett et al. (2014) use excitement and anxiety keyword dictionaries to measure changes in feelings about Fannie Mae and Enron over time, as reflected in financial narratives and e-mails. Most recently, Nyman et al. (2021) employ excitement and anxiety word lists to show the shift in sentiment prior to the Global Financial Crisis.

To construct our market emotion index, we start by cleaning the news articles. We convert all words to lower case, and remove numerical values, punctuation, symbols, tables, figures, and standard English stop words (e.g., a, an, and the etc.) in line with the natural language processing and the textual analysis literature. We generate emotion word counts using the two Taffler et al. (2021) keyword lexicons of excitement and anxiety. We generate our market emotion index ($MEI$) measure as:[9]

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

where $Excitement_t$ and $Anxiety_t$ are the respective excitement and anxiety word counts derived from news articles in month $t$ relative to the total number of words across the articles. Individual words receive equal weights.[10]

[9] Traditional tone and sentiment measures use valence. Following the circumplex model of emotions and object relations theory, we focus on emotional intensity/arousal. In a robustness test, we demonstrate that arousal is more powerful than valence (see Table A3).

[10] 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 computational linguistics procedures for our purposes, such as machine learning, can render out-of-sample tests fragile, and more likely to capture data artifacts (Loughran and McDonald, 2020). Also, it is not clear how machine learning can identify different types of emotion in a text as opposed to narrative tone. Hence, we choose simplicity and transparency over potential more elaborate alternatives to extract emotions from news items.

We do not use the Loughran and McDonald (2011) (LM) and Henry (2008) (HN) positive/negative word dictionaries in our main analysis (we use these in our robustness tests) for two reasons. First, these 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 that were profitable. Thus, words such as 'adverse', 'loss', 'impairment', and 'missing' do not appear in her negative dictionaries. Importantly, controlling for both Loughran and McDonald (2011) and Henry (2008) narrative tone measures in our robustness tests, we find investor emotional states have distinct predictive ability over and above such valency-based positivity/negativity measures.

*3.3. Validation tests: Are we capturing emotions or something else?*

Previous studies use indirect proxies for emotions. Laboratory-based experiments, for example, use video clips to exogenously induce, and facial recognition technology to detect, emotions (e.g., Andrade et al., 2016; Breaban and Noussair, 2018). In our case we extract our excitement and anxiety measures directly from news stories. In spirit, we follow Kaplanski and Levy (2010) who show how the media reflects people's anxiety associated with aviation disasters, which affects asset prices.

*3.3.1 Correlation with alternative measure, sentiment, volatility, uncertainty, and tone*

Our market emotion index is derived from excitement and anxiety word lexicons consisting of keywords with appropriate emotional meaning extracted directly from financial media using standard keyword-in-context based content analysis approaches. We compare our market emotion index with a similarly derived measure using the Tuckett et al. (2014) and Nyman et al. (2021) excitement and anxiety keyword dictionaries. These are constructed on an indirect basis employing psycholinguistic judgment to narrow down the Loughran and McDonald (2011) 10K-based positive and negative keyword dictionaries to words with emotional meaning then adding additional words that were intuitively relevant.

Using the same news items, the correlation between our MEI and the Nyman et al. (2021) measure using their dictionaries is 0.07.[11] Our emotions-based measure also differs from established sentiment measures. In fact, our market emotion index has correlations of only 0.02 and -0.03, respectively, with the Baker and Wurgler (2006) investor sentiment index and University of Michigan's Consumer Confidence Index. Panel A of Table 1 presents the correlations between our market emotion index and other measures. We also observe that our measure has very low correlation with a market-wide volatility measure (VIX), economic and policy uncertainty, and market-wide tone measures.

*3.3.2 Orthogonalization of market emotion index*

We note the news articles we use to construct our market emotion index may also reflect the concurrent state of the economy and macroeconomic uncertainty. We address this potential concern in several ways.

First, our search terms are designed specifically to identify news items directly associated with the stock market with a relevance score of 80% or more. Second, we re-estimate our market emotion index after removing words that are potentially related to the macroeconomy from our anxiety and excitement lexicons. Specifically, we drop 'uncertain' and 'uncertainty' from our anxiety keyword dictionary, and exclude 'boost', 'boosts', and

[11] Their measure also correlates at 0.88 with the parallel Loughran and McDonald (2011) tone measure using the same data, possibly reflecting the nature of its construction.

‘boosted’ from our excitement keyword dictionary.[12,13] In both cases, the resulting market emotion indices correlate at 0.97 with our main market emotion index.

Third, we orthogonalize our market emotion index in several ways. First, following Baker and Wurgler (2006), we orthogonalize by regressing our base MEI on several macroeconomic indicators and use the residuals as our first orthogonalized index ($MEI^{\perp}$). Macro variables are growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recession periods. Second, we estimate residuals by regressing our MEI on volatility, macro uncertainty, sentiment, and tone measures. These are the VIX, the economic uncertainty index of Jurado, et al. (2015, UNC), economic policy uncertainty index of Baker et al. (2016, EPU), investor sentiment of Baker and Wurgler (2006, BWSENT), the University of Michigan’s Consumer Confidence Index, and two positive-/negative-based tone measures of Loughran and McDonald (2011) and Henry (2008). The new set of residuals comprises our second orthogonalized index ($MEI^{\perp\perp}$). Third, we include indicators used in all of the indicators together and estimate residuals for our third orthogonalized index ($MEI^{\perp\perp\perp}$). All orthogonalized MEIs are very highly correlated (> 92%) with our base emotion index (see Panel A of Table 1).

Fourth, in our predictive regressions we control for the Jurado et al. (2015) economic uncertainty and Baker et al. (2016) economic policy uncertainty measures. Finally, we control for time-varying systematic risk exposures associated with business cycles and financial crises in our factor models. In this way we believe we are able to deal appropriately with both measurement-related concerns and economic confounding effects. We conclude our market emotion index measure is unlikely to be driven by macroeconomy related news and surprises.

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

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

*3.4. Estimating emotion beta*

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

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

where $R_{i,t}^{e}$ is the excess return on the stock $i$ in month $t$. We focus on $\beta_{i,t}^{MEI*}$, stock $i$'s emotion beta. $MEI_t$ is the monthly market emotion index. $MKT_t$ is the monthly excess market return. $X_t$ includes a set of asset pricing factors – size (SMB), book-to-market (HML), momentum (UMD), profitability (ROE), investment (I/A), expected growth (EG), liquidity (LIQ), finance (FIN), post-earnings announcement drift (PEAD), and betting against beta (BAB) at time $t$, respectively.[14]

To begin, we 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 $\beta^{MEI*}$ given by $\beta^{MEI} = \left|\beta_{i,t}^{MEI*}\right|$ under the assumption that stocks with higher emotional charge or utility for investors irrespective of valence will have higher $\beta^{MEI}$.

We focus on the magnitude of the conditional emotion beta for several reasons. First, emotional intensity represents 'arousal' in the circumplex model of affect (Posner et al., 2009)

[14] 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.

and increases with absolute value of valence which here relates to our emotion beta. Arousal represents the power of the emotions individuals experience that we expect to impact investor decision making in a predictable manner. Second, strength of the emotional charge ($\beta^{MEI}$) is more predictive 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).

Third, the nature of the ambivalent object relationships investors enter into with the stock market and individual stocks mean they will be experiencing feelings of excitement and anxiety at the same time. Investors invest in stocks believing that they will go up irrespective of their emotional states. Fourth, when the stock market is bullish, excited participants will act as trend chasers, and drive prices up further. In parallel, when the market is bearish with anxiety dominating, contrarian investors are likely to create price pressure. In both cases, stock prices go up generating mispricing, which eventually erodes as investors become more informed.

*3.5 Cross-sectional return predictors*

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.

The Fama-French factors, risk-free rate, and industry classification data are from Kenneth French's data library.[15] The Fama-French factor data includes the excess market return (MKT), small-minus-big (SMB), high-minus-low (HML), winner-minus-loser (UMD), robust-minus-

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

weak (RMW), and conservative-minus-aggressive (CMA) factors. The liquidity factor (LIQ) is from Lubos Pastor's data library. Other monthly factor returns such as profitability (ROE), investment (I/A), expected growth (EG), finance (FIN), post-earnings announcement drift (PEAD), and betting against beta (BAB), are downloaded from the global-*q* data library, Kent Daniel, and AQR websites.[16]

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

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:

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

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:

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

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

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

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

We also use market volatility. Like Ang et al. (2006), we estimate implied market volatility beta, 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:

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

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

Following Bali, Cakici, and Whitelaw (2011), and Bali et al. (2017), demand for lottery-like stocks, denoted MAX, is calculated as the average of the stock's five highest daily returns during month $t$. A stock is required to have at least 15 daily return observations during any given month to compute MAX.

As in Hou, Xue, and Zhang (2015), we compute the annual growth rate of total assets, denoted I/A, as the change in book assets scaled by lagged book assets. We also use annual operating profitability, denoted ROE, measured by income before extraordinary items scaled by one-year-lagged book equity. Following Ball et al. (2020), we present microcap adjusted results. 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 results

This section presents our main results. Our main goal is to assess the predictive power of firm-level emotion beta for future stock returns. We perform both cross-sectional and time-series tests and examine the robustness of our findings.

*4.1 Preliminary evidence*

We derive our market emotion index using news articles published in four widely circulated U.S. national newspapers and 17 local newspapers. We plot the original market emotion index (MEI) across time. Figure 1 shows that media reflects more emotional words leading up to the Internet bubble and the Global Financial Crisis periods.

Our market emotion index has several interesting properties. First, the market emotion index measures the emotional state of the stock market dynamically as reflected by the media which is different from investor sentiment. Second, we use both excitement and anxiety words in developing our market emotion index. As predictive by the circumplex model of emotions, the correlation between excitement and anxiety words is quite high and positive ($\rho$ = 0.36) – both excitement and anxiety contain incremental information beyond each other. Third, the index is easy to calculate and uses equal weights for its excitement and anxiety word counts as Jiang et al. (2019) and Henry and Leone (2016) demonstrate that simple equal weighting is as powerful as more sophisticated and complex weighting mechanisms. Fourth, our market emotion index can easily be developed for higher frequency data such as weekly or daily to capture transient changes in investor emotions. Finally, it can also be applied to other financial markets, asset classes, and extended far back in time. As we have shown, our market emotion index is also orthogonal to macroeconomy-related news and shocks.

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

*4.2 Fama and MacBeth regression estimates*

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

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

where $R_{i,t+1}^{e}$ is the realized excess return on stock $i$ in month $t + 1$, $\beta_{i,t}^{MEI}$ is the emotion beta of stock $i$ in month $t$, $\beta_{i,t}^{MKT}$ is the market beta of stock $i$ in month $t$, $\beta_{i,t}^{VIX}$ is the volatility beta of stock $i$ in month $t$, and $X_{i,t}$ is a collection of stock-specific control variables for stock $i$ in month $t$ (size, book-to-market, momentum, short-term reversal, illiquidity, idiosyncratic volatility, growth in assets, operating profitability, and lottery demand).[18]

Panel A of Table 2 reports Fama-MacBeth time-series averages of the slope coefficients with Newey-West $t$-statistics in parentheses. We find a positive and statistically significant relation between emotion beta and the cross-section of future stock returns even in the presence of all other control variables, i.e., higher emotion beta firms earn higher returns.

[18] We also report the correlation between emotion beta and firm characteristics in Table 1 Panel B. The stock-specific emotion beta has low but negative correlations with size, book-to-market, and operating profitability ($\rho$ = -0.14, -0.03, and -0.10). Emotion beta also has low positive correlations with momentum, reversal, idiosyncratic volatility, growth in assets, and lottery demand ($\rho$ = 0.05, 0.02, 0.12, 0.06, and 0.12). These low correlations with the firm specific risk factors provide initial evidence that emotion captures incremental information that can have important asset pricing implications.

For example, the average slope when we control for the market factor (see column 2) is 1.62 with a Newey-West $t$-statistic of 3.10.[19] To determine the economic significance of this average slope coefficient, we use the average values of the emotion sensitivities in the decile portfolios. Table 3 shows that the difference in emotion beta between high-minus-low decile portfolios is 0.39 (= 0.40 – 0.01) per month. If a stock were to move from the lowest to the highest decile of $\beta^{MEI}$, the change in the stock's average expected return would be a significant increase of 0.63% (= 1.62 × 0.39) per month.

Columns 2 to 6 control for other predictors and still the average slope coefficient of $\beta^{MEI}$ is positive and significant. In particular, the emotion sensitivity measure $\beta^{MEI}$ has an estimate of 0.69 with a $t$-statistic of 2.73 (see column 6). In economic terms, a one-standard-deviation shift in emotion beta is associated with a 0.88% (= 0.69 × 1.278) shift in stock return in the following month. These findings are similar when we control for industry effects in columns 7-12.

Overall, the Fama-MacBeth regression estimates are consistent with our first hypothesis, which posits that emotion beta positively predicts the cross-section of stock returns. Investors' integral emotions and associated object-relationships with stocks can explain return variation in the cross-section, and this effect is distinct from that of other well-known return predictors.

Panel B of Table 2 examines the long-term predictability of emotion beta and finds that the positive relation between emotion beta and future stock returns extends beyond one-month. The Fama-MacBeth regression estimates show that after controlling for different firm characteristics and risk factors, the average slope on emotion beta remains positive and

[19] Since our emotion beta has a correlation of 0.11 with market beta, it is arguable that the asset pricing effect we document is capturing some nonlinear market beta or volatility effect. To rule this out, we perform a placebo test as follows: we run a Fama-MacBeth regression with the market and volatility betas, but instead of our emotion beta, we include the absolute value of the market beta. We find the coefficient for the absolute value of the market beta is small and insignificant. This provides evidence that our results are independent of a market or volatility effect.

economically significant up to 5 months in the future. Based on this evidence, we conclude that a stock's emotional utility has a longer-term impact on returns.

*4.3 Univariate sorts*

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

Table 3 reports emotion beta portfolio characteristics. Average firm size (market capitalization in millions of dollars) almost monotonically decreases from low emotion beta to high emotion beta decile portfolios. 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 lower operating profitability (ROE), and higher market beta ($\beta^{MKT}$), growth in assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and lottery-like features (MAX). Across all characteristics the high emotion beta stock portfolio differs significantly from the low emotion beta portfolio.

It is the intrinsic nature of high emotion beta stocks that makes them ideal for grabbing investor attention and deriving emotion utility from. High emotion beta stocks have 'emotional glitter' creating price pressure and mispricing in the stock market.

Panel A of Table 4 reports portfolio average excess returns. Specifically, we examine whether high-minus-low emotion beta portfolios generate average excess returns across different return adjustment models. For each month, we form decile portfolios by sorting individual stocks based on their emotion betas ($\beta^{MEI}$) using different return adjustment models, where decile 1 (10) contains stocks with the lowest (highest) $\beta^{MEI}$ during the past month. In particular, we adjust stock returns for characteristics, market, and industry returns.

First, we present raw average excess returns. Second, following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW), we compute characteristics-adjusted returns. Third, we adjust market returns and use value-weighted index returns as the market return. Finally, we take into account Fama-French 48-industry returns. Average excess returns on the value-weighted portfolios are presented in columns 1-4, and the last row reports high-minus-low portfolio average excess returns.

In line with our main conjecture, we find that investors can earn economically significant average excess returns of 0.38-0.55% per month ($t$-statistics ranging from 2.11 to 2.86) by going long (short) in the undervalued (overvalued) high (low) emotion beta portfolios. The evidence is again consistent with investors deriving emotional utility from high emotion compared to low emotion beta stocks, and that this influences their investment decisions accordingly.

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

The first column of Table 4 Panel B shows that $\alpha_{FF5}$ increases from -0.03% to 0.50% per month. The difference in value-weighted alpha between the high-$\beta^{MEI}$ and low-$\beta^{MEI}$ decile portfolios is 0.53% per month (or 6.36% per annum) with a Newey-West $t$-statistic of 4.34. The other columns with different models show similar results. The alphas indicate that after controlling for well-known factors, the return difference between the high-$\beta^{MEI}$ and low-$\beta^{MEI}$ stocks remains positive and highly significant.

The last two columns of Table 4 Panel B present parallel evidence for $\beta^{MEI}$ value-weighted portfolios. Consistent with the results for $\alpha_{FF5}$ and $\alpha_q$, value-weighted $\alpha_{BS6}$ and $\alpha_{DHS3}$ alpha differences between high-$\beta^{MEI}$ and low-$\beta^{MEI}$ portfolios are also positive and significant: $\alpha_{BS6}$ = 0.55% per month ($t$-stat. = 3.96); and $\alpha_{DHS3}$ = 0.62% per month ($t$-stat. = 4.79).

These univariate sorting results support our key conjecture that high emotion beta stocks should earn higher returns than low emotion beta stocks. High-decile emotion beta stocks are small, growth, unprofitable, more volatile, illiquid, and lottery-like stocks, which are more difficult to value and thus more speculative, making them more emotionally charged and thus attractive to investors. such stocks are also hard to arbitrage rendering them prone to mispricing (Baler and Wurgler, 2006). Together, these stock characteristics generate price pressure and the economically significant alphas that we report.

*4.4 Alpha estimates using conditional factor models*

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

We report conditional alpha estimates and factor exposures in Table 5. Columns 1 to 6 control for the Fama-French five, momentum, and LIQ factors, and their interaction with each systematic risk factor respectively. The last two columns include the interaction of the Fama-French five, momentum, and LIQ factors with all the time-varying systematic risk factors at the same time. The last row presents the differences between high and low deciles.

We find that even after controlling for other conditional factors, the value-weighted high-minus-low portfolio alpha is economically significant across all models. For example, when we interact the Fama-French factors with NBER Recession, or with the *cay* residual, high-minus-low emotion beta portfolio alphas are 0.48% and 0.50%, respectively, with *t*-statistics of 3.70, and 4.06 (columns 1 and 3). Alpha remains significant when we take into account all the time-varying systematic risks simultaneously (columns 7 and 8). These estimates are very similar to the unconditional factor model alpha estimates of 0.53% and 0.55% in Table 4 Panel B (columns 1 and 3).

Overall, these conditional factor model estimates are similar to the results from the unconditional models. These findings again provide evidence in favor of our conjecture that the higher the emotional charge/beta, the higher is the stock return.

*4.5 Emotion beta persistence and alpha longevity*

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

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

Column 1 of the first row of Table 6 presents the univariate regressions of $\beta^{MEI}$ on previous 12 months' $\beta^{MEI}$. The coefficient is large and statistically significant, which implies that stocks with high $\beta^{MEI}$ exhibit a similar pattern in the following 12 months. We repeat the same process for up to 5 years ahead, and continue to find statistically significant results. The second row of Table 6 shows that after adding cross-sectional return predictors, coefficients remain large and significant. $\beta^{MEI}$ remains highly persistent up to 60 months into the future demonstrating the power of investors' integral emotions in driving their investment behavior.

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

Panel A of Figure 2 shows the effect of varying the portfolio formation lag from 1 to 24 months on monthly seven-factor abnormal returns. As the gap between portfolio formation period and portfolio return measurement period increases, the abnormal return becomes weaker, both in economic terms, and statistical significance. The abnormal return of high emotion beta stocks is corrected by the market in about 12 months. Not surprisingly, this evidence suggests that stock emotional charge decays over time.

We vary the holding period of the high-minus-low emotion beta-based portfolio in Panel B of Figure 2. Specifically, we hold the emotion-sensitive hedge portfolio for 3, 6, and 12 months, and rebalance portfolios accordingly. Similar to the findings in Panel A, we find for holding periods up to 10-months, a high-minus-low trading strategy generates significant alpha.

*4.6 Is emotion beta capturing something else?*

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

The correlation matrix in Appendix Table A2, shows that emotion beta is not highly correlated with mood, sentiment, uncertainty, or tone betas. In fact, the highest correlation is only 0.238 with mood beta. All other correlation coefficients are below 0.1. Thus, we have preliminary evidence that our fundamental emotion-based measure is capturing something distinct from mood, sentiment, uncertainty, and tone. To better understand how our integral emotion beta differs from such incidental emotion betas, we examine their individual relations in more detail.

*4.6.1 Is emotion beta capturing mood?*

To provide evidence that what our emotion beta is measuring is something other than mood, we first estimate mood beta following Hirshleifer et al. (2020). For each stock we run a 10-year rolling window regression of the stock's excess returns earned during pre-specified and realized high and low mood months ($R_{i,MoodMonth}$) on contemporaneous equal-weighted CRSP excess returns ($XRET_{A,MoodMonth}$):

$$R_{i,MoodMonth} = \alpha_i + \beta^{Mood}_{i,month} XRET_{A,MoodMonth} + \varepsilon_i, \tag{7}$$

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

Table 7, column 1 reports the results of the cross-sectional Fama-MacBeth regression, controlling for mood beta, firm characteristics, and other risk-factors. Even after accounting for mood beta, $\beta^{MEI}$ has a significant coefficient with a *t*-statistic of 2.06. In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 1.17% (= 0.92 × 1.278) shift in the stock's excess return in the following month. This result is not surprising as investors' fundamental emotions and their mood drive investment decisions in different ways. Mood is by definition unrelated to the decision at hand, whereas the emotions we are measuring are integral to the actual judgement (Lerner et al. 2015).

*4.6.2 Is emotion beta capturing sentiment?*

Next, we demonstrate that our emotion beta is distinct from measures of investor sentiment. We estimate two separate sentiment betas by running the following 60-month rolling window regressions for each stock's excess returns on the Baker and Wurgler (2006)[20] investor sentiment index orthogonalized for macro-variables, and the University of Michigan's consumer confidence index (UMCCI)[21], after controlling for the factors included in eq. (2) separately:[22]

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

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

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

Table 7 columns 2 and 3 presents Fama-MacBeth regression estimates, where we control for Baker and Wurgler and UMCCI sentiment betas. We find that emotion beta shows incremental economically significant predictive ability with coefficients of 0.52, and 0.53 and *t*-statistics of 2.41, and 2.36, respectively. Thus, emotion beta is different from sentiment betas and has incremental ability to explain the cross-sectional variation in returns.

*4.6.3 Is emotion beta capturing policy uncertainty?*

It is possible that economic and policy uncertainties are driving our results as high-(low-)levels of uncertainty may arouse feelings of anxiety (excitement) and/or negative (positive) sentiment. In addition, the news articles we use may include some economy-wide news that are intertwined with the stock market.

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

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

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

To examine this possibility, we control for the uncertainty beta of Bali et al. (2017), which is derived from the one-month ahead economic uncertainty index of Jurado et al. (2015). We estimate uncertainty beta by running a 60-month rolling window regression of each stock's excess returns on the uncertainty index, size (SMB), value (HML), momentum (MOM), liquidity (LIQ), investment (I/A), and profitability (ROE) factors:

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

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

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

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

Table 7 columns 4 and 5 report the Fama-MacBeth regressions controlling for the two uncertainty betas. Emotion beta has incremental predictive ability in both cases with coefficients of 0.50 and 0.49 and *t*-statistics of 2.15 and 2.23 respectively. Thus, we conclude that emotion betas do not capture the effects of economic uncertainty.

*4.6.4 Is emotion beta capturing tone?*

We further show that our market emotion index is distinct from popular text-driven tone measures based on the positive/negative word dictionaries of Loughran and McDonald (2011) and Henry (2008) applied to the same news articles we use to derive MEI.[23]

First, we explore for potential commonality across LM's positive/negative and our emotion-based word lists. Table A4 presents the 10 most frequently used emotional and tonal words in our corpus. In the case of 'excitement' and 'positive' words, only "boost" and "confident" are common, while only "fear" and "volatile" are common in the 'anxiety' and 'negative' word lists. These top 10 word counts suggest there is little similarity between the two sets of lexicons, and that emotion and tone may be measuring different things.

Next, we assign our news articles across MEI and tone score quintiles in Table A5. If both MEI and tone are measuring the same thing, then the diagonal elements should account for most of the news articles. However, the diagonal elements only account for 23.3% of the articles in total, demonstrating that the market emotion index and tone are measuring different dimensions of information.

Third, to reinforce further this point, we present two sample news articles that have very different emotional and tonal scores (in Appendix B). The first article (*The New York Times*, November 29, 2009) elicits emotions of excitement and anxiety and with the market emotion index score = 0.09, well in the top quartile of all MEIs (Table 1, Panel A). However, the LM tone is neutral with a score of 0.0. Careful reading shows that the stock market is doing well which investors are likely to experience as exciting but, there are reasons to be anxious with this equally feeding into their economic decisions.

The second article (*The Wall Street Journal*, January 13, 2004) has a market emotion index = 0.08, again well within the top quartile, reflecting the emotional charge conveyed by the news.

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

Again, the reasons for the high MEI are clear in the first sentence of the article: "After seven weeks of market gains, stocks began the new week with yet another advance amid optimism about coming fourth-quarter earnings reports". Nonetheless, LM tone remains neutral (= 0.00). These two news articles illustrate how the market emotion index and tone are measuring quite different things.

Finally, we estimate tone beta using the following specifications, and examine whether emotion beta still has any incremental predictive ability in the presence of tone betas. Specifically, we estimate a 60-month rolling window regression for each stock's excess returns on LM and HN tone respectively, after controlling for factors listed in eq. (2):

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

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

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

Table 7, columns 6 and 7 report the results of the two cross-sectional regressions. Again, even after accounting for the LM and HN tone measures $\beta^{MEI}$ still has significant coefficients (*t*-statistics = 2.28 and 2.34 respectively). In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 0.65% (= 0.51 × 1.278) shift in the stock's excess return in the following month. We confirm the stock's emotional charge is capturing something quite different from various positive/negative tone measures.

Finally, when we include all the mood, sentiment, uncertainty, and tone betas together in a multivariate Fama-MacBeth regression, we still find emotion beta to have economically significant predictive ability (see columns 8 and 9). Based on the results in Table 7, we conclude that emotion beta's ability to explain the cross-section of future stock returns is distinct from the known effects of mood, sentiment, uncertainty, and narrative tone.

*4.7 Bivariate sorts*

In previous subsections we do not control for different firm characteristics when constructing portfolios and estimating alphas. This subsection examines the relation between emotion beta and future stock returns in more detail by performing bivariate portfolio sorts. 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 deciles based on SIZE and then, within each SIZE decile, we sort stocks into further deciles based on B/M so that decile 1 (decile 10) contains stocks with the lowest (highest) market capitalization and book-to-market values.

Table 8, Panel A presents the average emotion beta across the bivariate deciles. Stocks with small market capitalization have greater emotional utility for investors than stocks with large market capitalization. Similarly, growth stocks have higher emotional resonance than value stocks. Taken together, average $\beta^{MEI}$ for decile (1,1) is double that for decile (10,10) demonstrating how small growth stocks carry a much greater emotional charge for investors than larger value stocks, consistent with the finding that hard to value stocks drive the high-minus-low average excess returns and alphas.

Next, we examine the relation between emotion beta and future stock returns after controlling for different firm characteristics. Specifically, we perform bivariate portfolio-level analysis of emotion beta stocks using the following five firm characteristics and market beta: market capitalization (SIZE), book-to-market (B/M), gross profitability (GP), illiquidity (ILLIQ), and idiosyncratic volatility (IVOL). Table 8 also reports the results of the conditional bivariate sorts between individual firm characteristics and emotion beta in Panel B. We report value-weighted seven-factor alphas relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors.

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

The first column in Panel B of Table 8 shows that after controlling for SIZE, the equal-weighted difference in the abnormal return spread between high and low emotion beta small stocks is 0.32% per month with a $t$-statistic of 2.23. Thus, firm size cannot explain the high (low) returns earned by high (low) emotion-sensitive stocks.

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

### *4.8 Emotion beta factor*

Our evidence so far demonstrates the key role emotion beta plays in predicting the cross-sectional variation in individual stock returns. In this section, we investigate whether investor emotion represents a new mispricing factor by examining whether existing well-known asset pricing factor models can explain the returns generated by an emotion beta-based factor.

We form our emotion beta factor (EMO) following Daniel, Hirshleifer, and Sun (2020). At the end of each month, we divide firms into two size groups (small “S” and big “B”) based on whether the firm’s market capitalization is below or above the CRSP median breakpoint.

Independently, we sort firms into one of the three emotional utility groups (low "L", middle "M", or high "H") based on their conditional emotion beta using the CRSP 20th and 80th percentile values of $\beta^{MEI}$. We form six portfolios (SL, SM, SH, BL, BM, and BH) based on the intersections of size and emotion beta groups. Emotion beta factor returns each month are 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., $EMO = (r_{SH} + r_{BH})/2 - (r_{SL} + r_{BL})/2$.

Table 9 shows the results of our spanning tests, where we estimate the emotion beta factor alpha by estimating the intercept from a regression of EMO factor return on several factor models – Fama and French (2015, FF5), Hou et al. (2015, *q*-factor and extended *q*-factor), Barillas and Shanken (2018, BS6), and Daniel et al. (2020, DHS3). We find that the alphas remain positive, in Panel A, ranging from 0.27% to 0.35%, and significant with *t*-statistics ranging from 2.71 to 3.33. We find qualitatively similar results when the emotion beta factor is constructed with value-weighted returns (Panel B). These results indicate that well-known asset pricing factor models cannot explain the return earned by our emotion-based factor.

Harvey, Liu, and Zhu (2016) suggest that a five percent level of significance for a new factor is too low a threshold, and argue for stricter requirements with a *t*-statistic greater than 3.0. Table 2 shows that our emotion beta factor in the Fama-MacBeth cross-sectional regressions meets this hurdle in most of the cases with *t*-statistics ranging between 2.73 and 3.94, and only dropping below this level controlling for all the risk factors with industry effects with a *t*-statistic of 2.25. In parallel, we find in Table 4 that the value-weighted emotion beta alphas passe this test easily with *t*-statistic of ranging from 3.33 to 4.79. With virtually all *t*-statistics greater than 3.00 in our conditional factor model analyses, we also provide evidence that emotion beta-based alpha is not affected by time varying U.S. systematic risks.

## 5. Additional results

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

### *5.1 Alternative measures of emotion beta*

To begin, we test whether alternative measures of emotion sensitivity ($\beta^{MEI}$) predict future stock returns. In our baseline analysis, we control for 11 factors in generating emotion beta using equation (2). It is possible that with a different set of control variables we may find no mispricing or predictability as we have degrees of freedom in choosing the right-hand side variables.

To test this possibility, we use three alternative measures of $\beta^{MEI}$. First, we control only for the market (MKT), size (SMB), value (HML), momentum (MOM), and liquidity (LIQ) factors, then the market (MKT), size (SMB), investment (IVA), and operating profitability (ROE) factors, and finally, following Bali et al. (2017), the market (MKT), size (SMB), value (HML), momentum (MOM), investment (I/A), profitability (ROE), and liquidity (LIQ) factors:

Model 1:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{a}} + \beta_{i,d}^{MKT} MKT_{t} + \beta_{i,t}^{SMB} SMB_{t} + \beta_{i,t}^{HML} HML_{t} + \beta_{i,t}^{MOM} MOM_{t} + +\beta_{i,t}^{LIQ} LIQ_{t} + \varepsilon_{i,t}, \quad (14)$$

Model 2:

$$R_{i,t}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{b}} + \beta_{i,t}^{MKT} MKT_{t} + \beta_{i,t}^{SMB} SMB_{t} + \beta_{i,t}^{IVA} I/A_{t} + \beta_{i,t}^{ROE} ROE_{t} + \varepsilon_{i,t}, \quad (15)$$

Model 3:

$$R_{t+1}^{e} = \alpha_{i,t} + \beta_{i,t}^{MEI^{c}} MEI_{t} + \beta_{i,t}^{MKT} MKT_{t} + \beta_{i,t}^{SMB} SMB_{t} + \beta_{i,t}^{HML} HML_{t} + \beta_{i,t}^{MOM} MOM_{t} +$$

$$\beta_{i,t}^{IVA} I/A_{t} + \beta_{i,t}^{ROE} ROE_{t} + \beta_{i,t}^{LIQ} LIQ_{t} + \varepsilon_{i,t}, \quad (16)$$

After generating $\beta^{MEI^a}$, $\beta^{MEI^b}$, and $\beta^{MEI^c}$ from these three specifications, we form value-weighted portfolios and compute factor alphas for each emotion beta decile. Models 1, 2, and 3 of Table 10 show that for all models, $\beta^{MEI}$ produces positive and significant alpha for value-weighted portfolios. The results presented in Table 10, along with those reported in Table 4, indicate that even using alternative specifications to measure firm-level emotional utility, emotion beta remains a significant predictor of future stock returns.

### *5.2 Orthogonalized market emotion indices*

In the next set of tests, we examine the performance of high-minus-low emotion beta-based trading strategies. In these tests, we estimate stock emotion betas employing 60-month rolling regression similar to that of equation (2) only replacing our original market emotion index with orthogonalized market emotion indices. Following Baker and Wurgler (2006), we use different macroeconomy-related indicators to orthogonalize the market emotion index and estimate emotion beta. We then test the performance of a high-minus-low emotion beta-based trading strategy.[24]

Table 11 presents the results from using different orthogonalized versions of the market emotion index. A high-minus-low emotion beta investment strategy generates a positive and significant alpha irrespective of the orthogonalization procedure and factor models used to estimate alphas. These results show that emotion beta-based mispricing is robust, and our measure is free from any macroeconomic confluence.

### 5.3 Subsample estimates

Next, we investigate if the emotion beta premium is driven by smaller, illiquid, or low-priced stocks. Specifically, we test whether the trading strategy of going long in high emotion beta

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

stocks and shorting low emotion beta stocks still generates a premium for S&P 500 stocks, the largest 1,000 stocks based on market capitalization, and 1,000 most liquid stocks based on Amihud's (2002) illiquidity measure. Panel A of Table 12 presents the respective FF5, *q*-factor, BS6, and DHS3 alpha spreads between high-$\beta^{MEI}$ and low-$\beta^{MEI}$ portfolio returns. In the case of S&P 500 stocks, this spread ranges from 0.52% to 0.63% per month (*t*-statistic from 2.85 to 4.12), 0.53% to 0.62% per month (*t*-statistic from 3.06 to 4.33) for the largest 1,000 stocks, and 0.44% to 0.48% per month (*t*-statistic from 2.58 to 3.73) for the 1,000 most liquid stocks. Thus, our evidence of emotion premium is not exclusive to small, illiquid, and low-priced stocks.

*5.4 Subperiod estimates*

It is arguable that the impact of investor emotion-based stock beta is related to different phases of the business cycle. Might investors only be emotional during up or down phases of the economy. If this is the case, then we will only observe significant emotion beta-based trading strategy alphas in either expansion or in recession periods. However, in this paper, we argue that investors are continually searching for an emotional 'fix' irrespective of economic conditions. Thus, we expect a high-minus-low emotion beta-based trading strategy to earn economically significant alphas in all periods.

Specifically, we divide our full sample into crisis and non-crisis periods. Our crisis periods include both NBER recessions and broadly defined dot.com bubble (October 1998 to September 2002) and Global Financial Crisis (January 2006 to June 2011) periods. We report the results in the first part of Panel B of Table 12. We find that a high-minus-low emotion beta trading strategy generates economically significant alpha after controlling for well-known asset-pricing factors in both crisis and non-crisis periods alike. These results provide evidence that investor emotion impacts investor decision making in general.

We then examine whether emotion-based alpha is only significant in periods of high or low sentiment. We split stocks based on the median of the Baker and Wurgler (2006) investor sentiment index. High (low) sentiment periods are defined by the months in which the Baker and Wurgler (2006) index is greater (lower) than its median value over the full sample period. The second part of Panel B of Table 12 shows that the high-minus-low trading strategy generate economically significant alphas during both high and low sentiment periods.

Taken together, these results provide evidence consistent with our assertion that investor emotion is a powerful and influential driver of portfolio decisions. The impact of investor emotion is uniform and does not depend on economic condition or sentiment. Thus, we argue, our emotion beta measure is able appropriately to identify investor emotional sensitivity to stocks leading to the related mispricing we find in the broad cross-section of the U.S. stock market.

*5.5 Extreme portfolio alphas*

All our portfolio level analysis so far has been based on decile portfolios. In this subsection, we determine whether the high-minus-low trading strategy alpha is robust across different portfolio composition choices. We construct a series of Long-Short portfolios sorted from tercile to decile. Figure 3 displays their extreme portfolio alphas. Each Long-Short portfolio alpha controls for the standard 7 factors: market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ). Figure 3 shows how across all portfolios, a Long-Short investment strategy generates economically and statistically significant alphas. We conclude our results are not driven by a specific choice for portfolio composition.

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

## 6. Summary and Conclusions

Casual observation of investors in financial markets indicates that investor emotions are influential in driving their investment decisions. We show the emotional engagement of investors with certain subsets of stocks appears to influence their decision making and systematically affect the composition of their investment portfolios. Depending on the strength of this relation this, in turn, influences asset prices in those market segments that are emotion sensitive. In this study, we focus on the integral emotions of excitement and anxiety, and show that the emotional utility investors derive from holding certain types of stocks influence the returns of emotion-sensitive stocks.

We propose a novel method to measure investor anxiety and excitement, and identify market segments that are more likely to be influenced by changes in these emotions. Using our stock emotion-sensitivity measure, we demonstrate that returns in the market segments with high emotion-sensitivity are predictable. A Long-Short emotion beta-based trading strategy generates an annualized alpha ranging from 6.36% to 7.44% during the 1995-2018 period. This evidence of predictability is robust and extends up to 5-10 months following the portfolio formation date.

Our evidence of predictability is distinct from other forms of predictability identified in the related literature on investor sentiment. In particular, our integral emotion-based predictability differs from the evidence of incidental emotion-based predictability. Specifically, we document return predictability even in the presence of mood, sentiment, economic and policy uncertainty, and tone-based measures. This result is in line with the emotions and decision-making theory that highlights the direct impact of integral emotions on decision making (Posner et al., 2005; Posner et al., 2009; Auchincloss and Samberg, 2011; Lerner et al., 2015).

Overall, our results establish a link between investor emotions and asset prices. In future work, it would be interesting to examine whether variations in investor emotions influence other dimensions of asset prices. For example, it may be interesting to examine whether retail and institutional investors overweight emotion-sensitive firms in different ways, and consequently do worse or better. Similarly, analysts and fund managers could develop emotional relationships with the firms they cover, and also separately identify those stocks that are most likely to be affected by investor emotions. It would also be useful to investigate how analysts adjust their forecasts in response to these emotional connections.

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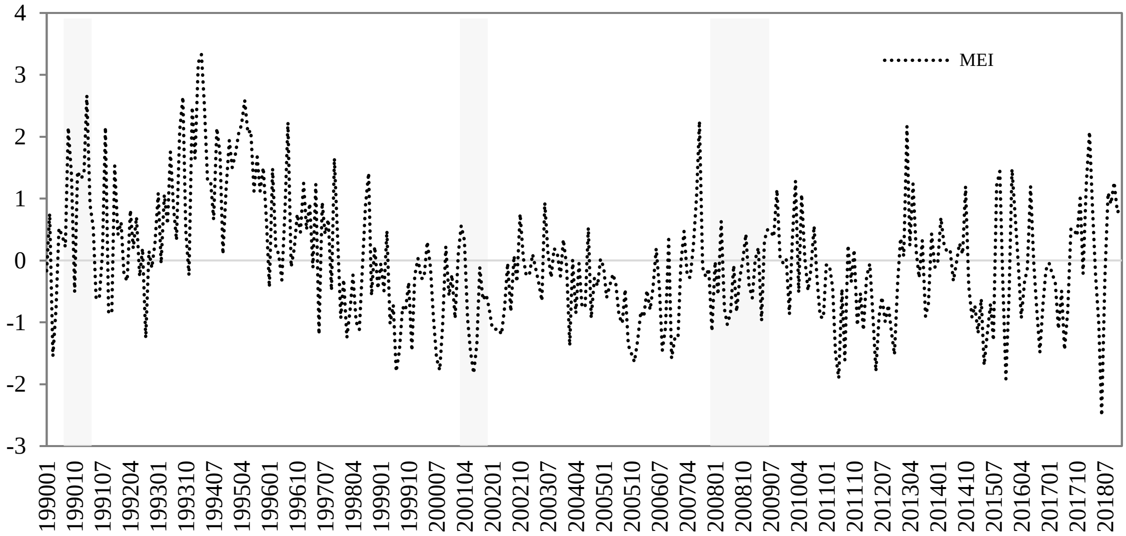


**Figure 1: Market Emotion Index over time**. The figure shows the market emotion index (MEI) over time. Market emotion index is measured as the ratio of total of excitement and anxiety word counts to the total word counts. We use news articles over a month to get the monthly word counts for excitement, anxiety, and total words. The shaded areas represent NBER recession periods. The sample period is from January 1990 to December 2018.

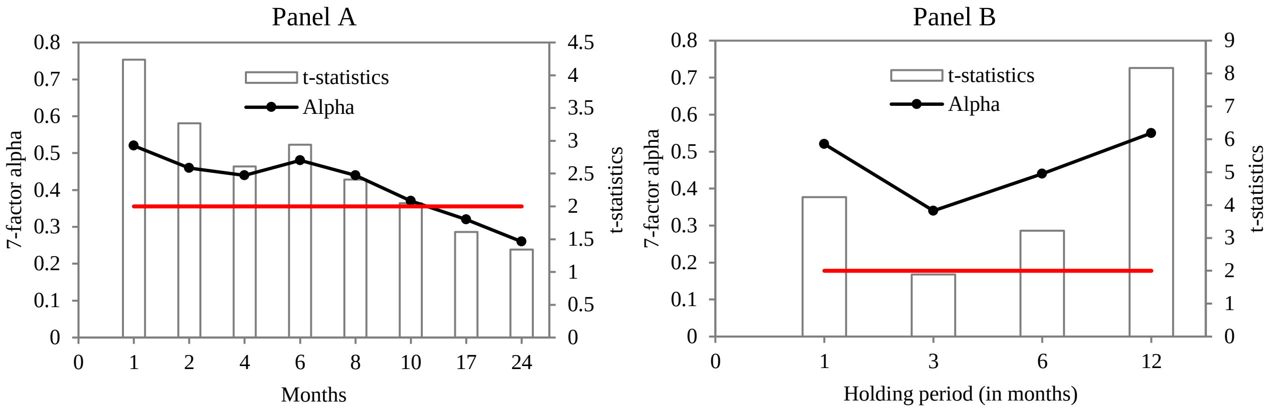


**Figure 2: Longevity of alpha.** The figure presents a series of Long-Short trading strategy alphas for different portfolios formed on emotion beta ($\beta^{MEI}$). For each month, we form portfolios based on emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) $\beta^{MEI}$ during the previous formation months. In Panel A, we examine the longevity of high-minus-low emotion beta-based trading strategy alphas. We keep on increasing the gap between the portfolio formation and emotion beta portfolio return estimation month. In Panel B, we hold emotion beta-based portfolios for different holding periods ranging from 1 to 12 months. The seven-factor alphas are relative to market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ) factors. The black line indicates 7-factor alphas and columns represent Newey-West *t*-statistics for respective alphas. The red line represents *t*-statistics at 2.00. The estimation period is from January 1995 to December 2018.

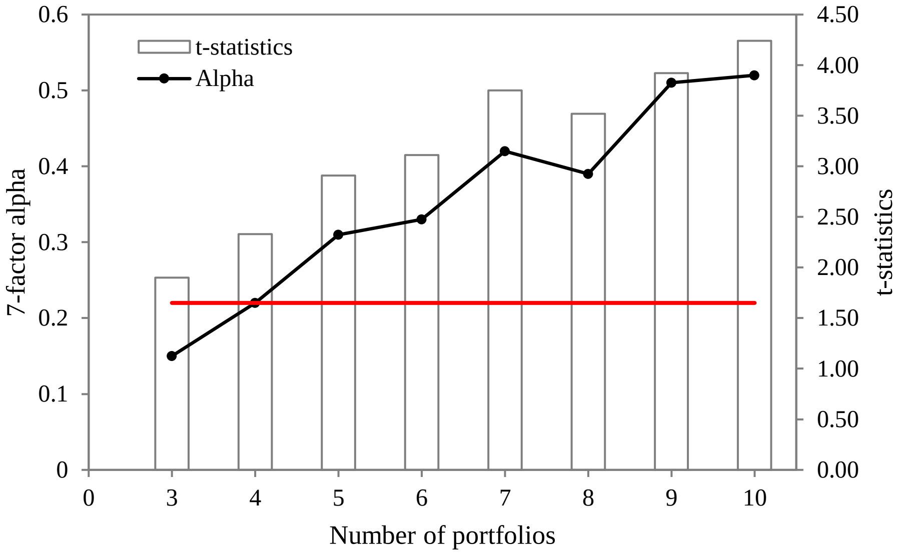


**Figure 3: Extreme portfolio alpha.** The figure presents a series of emotion beta-based Long-Short trading strategy alphas and their associated *t*-statistics. For each month, we form portfolios ranging from tercile to decile by sorting stocks based on their emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) $\beta^{MEI}$ during the previous formation months. The seven-factor alphas are relative to market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ) factors. The black line indicates 7-factor alphas and columns represent Newey-West *t*-statistics for respective alphas. The red line represents *t*-statistic at 90% confidence level. The estimation period is from January 1995 to December 2018

**Table 1: Correlation analysis and summary statistics**

The table reports correlation between and summary statistics of key variables. Panel A presents correlation analysis between market emotion index (MEI), its orthogonalized variations, volatility, macro-wide sentiment, economic and policy uncertainty, and textual tone measures. Market emotion index is measured as the ratio of total of excitement and anxiety word counts to the total word counts from 21 newspaper articles in a month. We use news articles over a month to get the monthly word counts for excitement and anxiety. Following Baker and Wurgler (2006), we construct three orthogonalized MEIs ($MEI^{\perp}$, $MEI^{\perp\perp}$, and $MEI^{\perp\perp\perp}$) by collecting residuals from regressions of MEI on (i) macroeconomy related indicators (growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions); (ii) macro uncertainty and tone measures (VIX, economic uncertainty index (Jurado, Ludvigson, and, Ng, 2015, UNC), economic policy uncertainty index (Baker, Bloom, and Davis, 2016, EPU), investor sentiment (Baker and Wurgler, 2006, BWSENT), University of Michigan's Consumer Confidence Index, and two positive-/negative-based tone measures (Loughran and McDonald, 2011, LN; Henry, 2008, HN); and (iii) including both listed in (i) and (ii). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries, respectively. Panel B shows the correlation between firm-specific emotion beta and other firm characteristics. The emotion beta ($\beta^{MEI}$) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and asset pricing factors—market, size, value, momentum, liquidity, investment, profitability, finance, post earnings announcement drift, betting against beta. We then take absolute value of emotion beta. Panel C reports the mean, standard deviation, 25th percentile, median, and 75th percentile of the market emotion index (MEI), emotion beta ($\beta^{MEI}$), and other firm characteristics. Firm characteristics are SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of assets (I/A), operating profitability (ROE), and demand for lottery-like stocks (MAX). The estimation period is from January 1990 to December 2018.

Panel A: Correlation between MEI and other measures

| | MEI | $MEI^{\perp}$ | $MEI^{\perp\perp}$ | $MEI^{\perp\perp\perp}$ | VIX | BWSENT | UMCCI | UNC | EPU | LM | HN |
|---|---|---|---|---|---|---|---|---|---|---|---|
| MEI | 1 | 0.964 | 0.951 | 0.924 | -0.044 | 0.019 | -0.028 | -0.203 | -0.027 | 0.080 | 0.002 |
| $MEI^{\perp}$ | | 1 | 0.936 | 0.971 | -0.018 | 0.060 | -0.053 | -0.132 | -0.038 | 0.018 | -0.030 |

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

| | $\beta^{MKT}$ | $\beta^{VIX}$ | SIZE | B/M | MOM | REV | ILLIQ | IVOL | I/A | ROE | MAX |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta^{MEI}$ | 0.106 | 0.018 | -0.136 | -0.031 | 0.049 | 0.018 | -0.002 | 0.125 | 0.058 | -0.102 | 0.123 |

Panel C: Summary statistics

| | MEI | $\beta^{MEI*}$ | $\beta^{MEI}$ | SIZE | B/M | MOM | REV | ILLIQ | IVOL | I/A | ROE | MAX |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 0.042 | -0.010 | 0.135 | 3409.46 | 0.648 | 0.179 | 0.011 | 0.046 | 0.019 | 0.133 | 0.075 | 0.031 |
| Standard deviation | 0.514 | 1.862 | 1.278 | 7111.911 | 0.714 | 0.563 | 0.136 | 1.187 | 0.013 | 0.469 | 0.949 | 0.021 |
| 25th percentile | 0.039 | -0.011 | 0.043 | 252.602 | 0.319 | -0.103 | -0.052 | 0.000 | 0.011 | -0.009 | 0.037 | 0.018 |
| Median | 0.042 | -0.050 | 0.098 | 847.32 | 0.523 | 0.103 | 0.007 | 0.000 | 0.016 | 0.062 | 0.095 | 0.026 |
| 75th percentile | 0.045 | 0.090 | 0.187 | 2888.619 | 0.809 | 0.339 | 0.068 | 0.003 | 0.024 | 0.164 | 0.159 | 0.038 |

## Table 2: Fama-MacBeth cross-sectional regression estimates

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion beta ($\beta^{MEI}$) and a set of lagged control variables using the Fama-MacBeth method. The control variables are market beta ($\beta^{MKT}$), volatility beta ($\beta^{VIX}$), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). Panel B presents the results from regressing monthly excess returns in two- to 6-months ahead against $\beta^{MEI}$ after controlling for all other predictive variables and for brevity, we do not report their intercepts, and coefficients. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Monthly Fama-MacBeth regression estimates

| | Without industry effects | | | | | | With industry effects | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| $\beta^{MEI}$ | 1.68 | 1.62 | 1.67 | 1.30 | 1.12 | 0.69 | 1.26 | 1.23 | 1.25 | 0.88 | 0.78 | 0.51 |
| | (3.01) | (3.10) | (3.23) | (3.43) | (3.33) | (2.73) | (3.25) | (3.94) | (3.31) | (3.06) | (2.97) | (2.25) |
| $\beta^{MKT}$ | | 0.12 | 0.09 | 0.02 | -0.01 | -0.01 | | 0.08 | 0.04 | -0.02 | -0.03 | -0.02 |
| | | (1.10) | (0.79) | (0.26) | (-0.04) | (-0.04) | | (0.92) | (0.51) | (-0.24) | (-0.45) | (-0.24) |
| $\beta^{VIX}$ | | | -0.33 | -0.48 | -0.50 | -0.40 | | | -0.22 | -0.37 | -0.40 | -0.33 |
| | | | (-1.18) | (-1.72) | (-1.86) | (-1.43) | | | (-1.03) | (-1.70) | (-1.88) | (-1.46) |
| SIZE | | | | -0.33 | -0.32 | -0.22 | | | | -0.29 | -0.29 | -0.21 |
| | | | | (-4.29) | (-4.53) | (-3.34) | | | | (-4.14) | (-4.49) | (-3.37) |
| B/M | | | | 0.40 | 0.46 | 0.45 | | | | 0.61 | 0.66 | 0.59 |
| | | | | (3.06) | (3.40) | (3.84) | | | | (5.68) | (6.17) | (5.88) |
| MOM | | | | -0.03 | -0.14 | -0.15 | | | | -0.03 | -0.13 | -0.14 |
| | | | | (-0.15) | (-0.62) | (-0.70) | | | | (-0.16) | (-0.66) | (-0.75) |
| REV | | | | | -1.21 | -1.11 | | | | | -1.33 | -1.28 |
| | | | | | (-1.95) | (-1.93) | | | | | (-2.44) | (-2.47) |
| I/A | | | | | 0.24 | 0.21 | | | | | 0.17 | 0.17 |
| | | | | | (1.82) | (1.69) | | | | | (1.49) | (1.50) |
| ROE | | | | | 0.40 | 0.64 | | | | | 0.54 | 0.72 |
| | | | | | (1.23) | (2.32) | | | | | (1.94) | (2.92) |
| ILLIQ | | | | | | 0.29 | | | | | | 0.29 |
| | | | | | | (6.12) | | | | | | (6.03) |
| IVOL | | | | | | 0.56 | | | | | | 0.55 |
| | | | | | | (7.01) | | | | | | (7.44) |
| MAX | | | | | | -0.18 | | | | | | -0.20 |
| | | | | | | (-2.86) | | | | | | (-3.44) |
| Intercept | 1.06 | 0.95 | 1.03 | 0.96 | 0.86 | 0.39 | 0.99 | 0.57 | 1.00 | 0.60 | 0.41 | 0.13 |
| | (4.00) | (4.39) | (4.61) | (3.71) | (3.21) | (1.64) | (2.85) | (1.82) | (3.55) | (1.97) | (1.16) | (0.44) |
| Adj. R-squared | 0.55% | 1.30% | 1.74% | 3.97% | 5.61% | 6.91% | 6.13% | 6.58% | 7.04% | 8.61% | 9.80% | 10.69% |
| N months | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 |

| Panel B: Long-term predictive ability of emotion beta | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Without industry effects | | | | | With industry effects | | | | |
| *n*-months ahead | *n* = 2 | *n* = 3 | *n* = 4 | *n* = 5 | *n* = 6 | *n* = 2 | *n* = 3 | *n* = 4 | *n* = 5 | *n* = 6 |
| $\beta^{MEI}$ | 0.74 | 0.52 | 0.67 | 0.53 | 0.36 | 0.56 | 0.44 | 0.55 | 0.42 | 0.30 |
| | (2.98) | (2.29) | (3.38) | (2.35) | (1.67) | (2.57) | (2.16) | (3.00) | (2.05) | (1.45) |
| Firm controls & risk factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-squared | 5.55% | 5.33% | 5.01% | 4.89% | 5.59% | 9.08% | 8.88% | 10.09% | 8.40% | 8.20% |
| N months | 286 | 285 | 284 | 283 | 282 | 286 | 285 | 284 | 283 | 282 |

**Table 3: Characteristics of emotion beta sorted portfolios**

The table reports the characteristics of portfolios sorted on emotion beta. For each month, we form decile portfolios by sorting stocks based on their emotion beta ($\beta^{MEI}$), where decile 1 (10) contains stocks with the lowest (highest) $\beta^{MEI}$ during the previous month. Columns 1 to 10 present the average emotion beta ($\beta^{MEI}$), market beta ($\beta^{MKT}$), SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), profitability (ROE), annual growth of assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and demand for lottery-like stocks (MAX) across portfolios. The last column presents the difference between high and low portfolios. All results are microcap adjusted. The estimation period is from January 1995 to December 2018.

| | Portfolios | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | High-Low |
| $\beta^{MEI}$ | 0.010 | 0.027 | 0.046 | 0.067 | 0.089 | 0.115 | 0.147 | 0.188 | 0.249 | 0.400 | 0.390 |
| | | | | | | | | | | | (29.02) |
| $\beta^{MKT}$ | 0.924 | 0.932 | 0.937 | 0.947 | 0.961 | 0.972 | 0.988 | 1.010 | 1.043 | 1.068 | 0.143 |
| | | | | | | | | | | | (9.93) |
| SIZE | 4463.316 | 4,498.995 | 4,374.165 | 4,188.450 | 3,933.738 | 3,492.738 | 3,073.037 | 2,619.450 | 2,111.345 | 1,455.542 | -3118.476 |
| | | | | | | | | | | | (-16.50) |
| B/M | 0.621 | 0.629 | 0.628 | 0.629 | 0.628 | 0.638 | 0.636 | 0.628 | 0.621 | 0.587 | -0.033 |
| | | | | | | | | | | | (-2.85) |
| ROE | 0.094 | 0.093 | 0.099 | 0.088 | 0.085 | 0.078 | 0.076 | 0.065 | 0.056 | 0.005 | -0.089 |
| | | | | | | | | | | | (-13.91) |
| I/A | 0.105 | 0.105 | 0.107 | 0.111 | 0.112 | 0.114 | 0.119 | 0.126 | 0.138 | 0.156 | 0.050 |
| | | | | | | | | | | | (9.22) |
| IVOL | 0.017 | 0.017 | 0.017 | 0.018 | 0.018 | 0.019 | 0.020 | 0.021 | 0.022 | 0.025 | 0.008 |
| | | | | | | | | | | | (23.73) |
| ILLIQ | 0.018 | 0.018 | 0.018 | 0.019 | 0.019 | 0.021 | 0.021 | 0.022 | 0.021 | 0.020 | 0.002 |
| | | | | | | | | | | | (1.77) |
| MAX | 0.027 | 0.028 | 0.028 | 0.029 | 0.029 | 0.030 | 0.031 | 0.033 | 0.035 | 0.039 | 0.011 |
| | | | | | | | | | | | (21.35) |

## Table 4: Performance of emotion beta sorted portfolios

The table presents portfolio average excess returns across different return adjustment models and unconditional factor model alphas. For each month, we form decile portfolios by sorting stocks based on their emotion beta ($\beta^{MEI}$), where decile 1 (10) contains stocks with the lowest (highest) $\beta^{MEI}$ during the previous month. In Panel A column 1, we present the value-weighted average excess returns. Column 2 reports the average value-weighted excess returns for characteristics adjusted returns of Daniel, Grinblatt, Titman, and Wermers (1997, DGTW). Column 3 adjusts for market returns in generating portfolio value-weighted average excess returns. Column 4 presents the value-weighted average excess returns after adjusting for Fama-French (1997) 48-industry returns. Panel B presents emotion beta-based portfolio alphas. Columns 1 to 4 report the alphas ($\alpha_{FF5}$, $\alpha_q$, $\alpha_{BS6}$, and $\alpha_{DHS3}$) controlling for Fama and French (2015, FF5) 5-factors, Hou, Xue, Zhang (2015, *q*-factor) 4-factors, Barillas and Shanken (2018, BS6) 6-factors, and Daniel, Hirshleifer, and Sun (2020, DHS3) 3-factors for value-weighted portfolios. The last rows in both the panels present results for high-minus-low portfolios. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Portfolio average excess returns across return adjustment models

| Portfolios | RET-RF | DGTW return | Market-adjusted return | Industry-adjusted return |
|---|---|---|---|---|
| Low | 0.72 | 0.02 | 0.08 | 0.06 |
| | (2.73) | (0.29) | (0.83) | (1.02) |
| 2 | 0.77 | 0.03 | 0.08 | 0.01 |
| | (2.89) | (0.40) | (0.86) | (0.34) |
| 3 | 0.73 | -0.04 | 0.04 | 0.03 |
| | (2.85) | (-0.59) | (0.35) | (0.49) |
| 4 | 0.81 | 0.02 | 0.06 | 0.05 |
| | (3.18) | (0.22) | (0.63) | (0.95) |
| 5 | 0.77 | 0.03 | 0.15 | 0.14 |
| | (2.98) | (0.39) | (1.48) | (1.92) |
| 6 | 0.74 | 0.05 | 0.06 | 0.05 |
| | (2.56) | (0.60) | (0.69) | (0.87) |
| 7 | 0.85 | 0.18 | 0.15 | 0.21 |
| | (3.05) | (1.97) | (1.28) | (2.39) |
| 8 | 0.82 | 0.07 | 0.09 | 0.08 |
| | (2.63) | (0.69) | (0.67) | (0.86) |
| 9 | 0.80 | 0.15 | 0.19 | 0.23 |
| | (2.25) | (1.20) | (1.17) | (1.84) |
| High | 1.27 | 0.40 | 0.63 | 0.52 |
| | (3.09) | (3.09) | (2.74) | (3.26) |
| High-Low | 0.55 | 0.38 | 0.55 | 0.46 |
| | (2.51) | (2.54) | (2.11) | (2.86) |

Panel B: Portfolio alphas using unconditional factor models

| Portfolios | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ |
|---|---|---|---|---|
| Low | -0.03 | 0.07 | 0.05 | 0.11 |
| | (-0.32) | (0.72) | (0.63) | (1.22) |
| 2 | -0.00 | 0.06 | 0.04 | 0.13 |
| | (-0.09) | (0.71) | (0.57) | (1.64) |
| 3 | -0.02 | 0.06 | 0.04 | 0.10 |
| | (-0.27) | (0.61) | (0.46) | (1.05) |
| 4 | 0.04 | 0.13 | 0.11 | 0.18 |
| | (0.45) | (1.34) | (1.37) | (2.07) |
| 5 | -0.02 | 0.04 | 0.02 | 0.13 |
| | (-0.24) | (0.47) | (0.30) | (1.66) |
| 6 | -0.03 | 0.08 | 0.06 | 0.17 |
| | (-0.36) | (0.88) | (0.69) | (1.89) |
| 7 | 0.03 | 0.07 | 0.05 | 0.18 |
| | (0.27) | (0.62) | (0.47) | (1.72) |
| 8 | 0.03 | 0.09 | 0.07 | 0.25 |
| | (0.22) | (0.66) | (0.51) | (1.97) |
| 9 | 0.15 | 0.22 | 0.22 | 0.33 |
| | (1.07) | (1.53) | (1.44) | (2.01) |
| High | 0.50 | 0.60 | 0.60 | 0.74 |
| | (3.74) | (3.95) | (3.96) | (4.74) |
| High-Low | 0.53 | 0.53 | 0.55 | 0.62 |
| | (4.34) | (3.33) | (3.96) | (4.79) |

**Table 5: Emotion beta sorted portfolios: conditional factor model estimates**

The table presents portfolio alphas based on conditional factor models. For each month, we form decile portfolios by sorting stocks based on their emotion beta ($\beta^{MEI}$), where decile 1 (10) contains stocks with the lowest (highest) $\beta^{MEI}$ during the previous month. The table present value-weighted portfolio alphas, after considering for Fama-French six factors, Pastor and Stambaugh's (2003) liquidity factor and time-varying U.S. systematic risk factors. The Fama-French factors include the market, size, value, momentum, profitability, and investment factors. The time-varying U.S. systematic risk factors are (i) the NBER recession indicator which takes the value of 1 during recession periods and 0 otherwise; (ii) alternatively, we use prolonged recession period (extreme market conditions, EXTMKT) for the dot.com bubble (October 1998 to September 2002) and Global Financial Crisis (January 2006 to June 2011); (iii) the *cay* residual of Lettau and Ludvigson (2001); (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 of the U.S. systematic risk factors. The last two columns include interaction with all the time-varying U.S. systematic risk factors with Fama-French and LIQ factors at the same time. The last row presents the difference between high and low portfolio alphas. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| Portfolios | $\alpha_{FF6+LIQ+REC}$ | $\alpha_{FF6+LIQ+EXTMKT}$ | $\alpha_{FF6+LIQ+cay}$ | $\alpha_{FF6+LIQ+pspd}$ | $\alpha_{FF6+LIQ+tspd}$ | $\alpha_{FF6+LIQ+dspd}$ | $\alpha_{all}$ | $\alpha_{all\ with\ EXTMK}$ |
|---|---|---|---|---|---|---|---|---|
| Low | 0.02 | -0.03 | -0.02 | 0.00 | 0.00 | -0.01 | 0.00 | 0.01 |
| | (0.21) | (-0.33) | (-0.26) | (0.00) | (0.06) | (-0.19) | (0.04) | (0.10) |
| 2 | 0.02 | -0.06 | -0.05 | -0.01 | -0.01 | -0.00 | 0.06 | 0.02 |
| | (0.37) | (-0.71) | (-0.55) | (-0.19) | (-0.14) | (-0.13) | (0.94) | (0.37) |
| 3 | -0.00 | -0.03 | -0.06 | -0.02 | -0.01 | -0.03 | -0.02 | -0.03 |
| | (-0.08) | (-0.32) | (-0.59) | (-0.18) | (-0.15) | (-0.26) | (-0.29) | (-0.32) |
| 4 | 0.06 | 0.05 | 0.02 | 0.04 | 0.05 | 0.02 | 0.00 | 0.03 |
| | (0.73) | (0.49) | (0.20) | (0.52) | (0.67) | (0.26) | (0.03) | (0.36) |
| 5 | 0.02 | -0.02 | -0.05 | -0.02 | -0.01 | 0.00 | 0.05 | 0.04 |
| | (0.26) | (-0.24) | (-0.55) | (-0.24) | (-0.07) | (0.06) | (0.61) | (0.48) |
| 6 | -0.02 | -0.06 | -0.05 | -0.03 | -0.03 | -0.06 | -0.03 | -0.05 |
| | (-0.23) | (-0.67) | (-0.49) | (-0.29) | (-0.32) | (-0.57) | (-0.32) | (-0.53) |
| 7 | 0.00 | 0.06 | -0.03 | -0.00 | -0.00 | 0.00 | 0.10 | 0.06 |
| | (0.02) | (0.53) | (-0.24) | (-0.02) | (-0.09) | (0.02) | (0.98) | (0.67) |
| 8 | -0.00 | 0.06 | -0.01 | -0.00 | 0.01 | -0.02 | 0.01 | 0.02 |
| | (-0.07) | (0.46) | (-0.14) | (-0.05) | (0.08) | (-0.20) | (0.12) | (0.17) |
| 9 | 0.12 | 0.01 | 0.13 | 0.14 | 0.15 | 0.11 | 0.13 | 0.13 |
| | (0.81) | (0.65) | (0.96) | (1.02) | (1.10) | (0.76) | (0.95) | (1.03) |
| High | 0.50 | 0.49 | 0.48 | 0.48 | 0.49 | 0.43 | 0.57 | 0.54 |
| | (3.47) | (3.41) | (3.40) | (3.24) | (3.38) | (2.88) | (3.37) | (3.37) |
| High-Low | 0.48 | 0.52 | 0.50 | 0.48 | 0.49 | 0.45 | 0.57 | 0.53 |
| | (3.70) | (4.00) | (4.06) | (3.62) | (3.66) | (3.39) | (3.56) | (3.16) |

**Table 6: Persistence in emotion beta**

The table presents results on the persistence of emotion beta. We examine the persistence of emotion beta ($\beta^{MEI}$) by running firm-level cross-sectional regressions of $\beta^{MEI}$ on lagged $\beta^{MEI}$ and lagged cross-sectional control variables. The first row reports average slope coefficients of univariate Fama-MacBeth regressions of 12-months to 60-months $\beta^{MEI}$ on lagged $\beta^{MEI}$. The last row presents the average slope coefficients after controlling for lagged variables: the market beta ($\beta^{MKT}$), market capitalization (SIZE), volatility beta ($\beta^{VIX}$), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth in book assets (I/A), operating profitability (ROE), and lottery demand (MAX). All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| *n*-year-ahead $\beta^{MEI}$ | *n* = 1 | *n =2* | *n = 3* | *n = 4* | *n = 5* |
|---|---|---|---|---|---|
| Univariate predictive regressions | 0.56 | 0.34 | 0.24 | 0.18 | 0.15 |
| | (40.86) | (28.43) | (21.05) | (16.53) | (12.90) |
| Controlling for lagged variables | 0.50 | 0.27 | 0.16 | 0.11 | 0.08 |
| | (33.59) | (21.65) | (15.58) | (12.05) | (9.12) |

**Table 7: Fama-MacBeth regression estimates using mood, sentiment, uncertainty, and tone betas**

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion, mood, sentiment, uncertainty, and tone betas along with a set of lagged control variables (used in Table 2) using Fama-MacBeth methodology. The emotion beta ($\beta^{MEI}$) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and a set of factors described in equation (2). Then, we take the absolute value of $\beta^{MEI}$. The mood beta ($\beta^{Mood}$) of Hirshleifer 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. 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 ($\beta^{SENT}$) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index and a set of factors listed in equation (2). We generate the consumer confidence beta ($\beta^{UMCCI}$) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and a set of factors described in equation (2). Following Bali et al. (2017), we compute the uncertainty beta ($\beta^{UNC}$) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta ($\beta^{EPU}$) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and a set of factors listed in equation (2). We derive two tone betas ($\beta^{LM}$ and $\beta^{HN}$) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and a set of factors described in equation (2). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries respectively. For brevity, we do not report the intercepts and coefficients of lagged control variables. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| $\beta^{MEI}$ | 0.92 | 0.52 | 0.53 | 0.50 | 0.49 | 0.51 | 0.51 | 0.51 | 0.86 |
| | (2.06) | (2.41) | (2.36) | (2.15) | (2.23) | (2.28) | (2.34) | (2.30) | (2.11) |
| $\beta^{Mood}$ | -0.23 | | | | | | | | -0.19 |
| | (-0.67) | | | | | | | | (-0.56) |
| $\beta^{SENT}$ | | 0.50 | | | | | | 0.13 | 0.12 |
| | | (0.53) | | | | | | (1.08) | (0.06) |
| $\beta^{UMCCI}$ | | | -0.07 | | | | | 0.89 | 0.92 |
| | | | (-0.05) | | | | | (0.37) | (2.00) |
| $\beta^{UNC}$ | | | | -0.02 | | | | -0.01 | -0.09 |
| | | | | (-0.21) | | | | (-0.12) | (-0.29) |
| $\beta^{EPU}$ | | | | | 0.58 | | | 2.17 | 1.36 |
| | | | | | (1.06) | | | (3.26) | (0.91) |
| $\beta^{LM}$ | | | | | | 0.19 | | 0.33 | -0.66 |
| | | | | | | (1.34) | | (1.16) | (-1.44) |
| $\beta^{HN}$ | | | | | | | 0.06 | 0.07 | 0.32 |
| | | | | | | | (0.28) | (0.15) | (0.48) |
| 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 | 14.22% | 10.81% | 10.79% | 10.77% | 10.78% | 10.81% | 10.81% | 11.29% | 14.83% |
| N months | 109 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 109 |

**Table 8: Emotion beta estimates for bivariate sorted portfolios**

The table shows results from bivariate sorts. Panel A reports average emotion beta ($\beta^{MEI}$) across size and book-to-market deciles. First, stocks are sorted based on SIZE (market capitalization) into decile portfolios and then, each of the SIZE deciles are sorted again on book-to-market. After bivariate sorting, the table reports average emotion beta across deciles. In Panel B, stocks are first sorted into deciles based on a firm characteristic, and then within each characteristic decile stocks are further sorted into deciles based on emotion beta ($\beta^{MEI}$). For each emotion beta decile, we average alphas across the ten characteristic groups. The firm characteristics are market capitalization (SIZE), book-to-market (B/M), gross profitability (GP), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), and market beta ($\beta^{MKT}$). We report value-weighted seven-factor alphas (in percentage) relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

Panel A: Average emotion beta across size and book-to-market

| | | SIZE | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Small | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Big |
| | Low | 0.19 | 0.19 | 0.18 | 0.18 | 0.17 | 0.16 | 0.14 | 0.13 | 0.11 | 0.10 |
| | 2 | 0.18 | 0.18 | 0.17 | 0.16 | 0.15 | 0.14 | 0.13 | 0.13 | 0.11 | 0.09 |
| | 3 | 0.16 | 0.16 | 0.16 | 0.15 | 0.14 | 0.14 | 0.13 | 0.12 | 0.11 | 0.09 |
| | 4 | 0.16 | 0.16 | 0.16 | 0.15 | 0.14 | 0.13 | 0.12 | 0.12 | 0.11 | 0.09 |
| B/M | 5 | 0.15 | 0.15 | 0.15 | 0.15 | 0.14 | 0.13 | 0.11 | 0.11 | 0.10 | 0.08 |
| | 6 | 0.15 | 0.15 | 0.15 | 0.14 | 0.13 | 0.12 | 0.11 | 0.11 | 0.10 | 0.08 |
| | 7 | 0.15 | 0.15 | 0.14 | 0.14 | 0.13 | 0.12 | 0.12 | 0.11 | 0.11 | 0.09 |
| | 8 | 0.15 | 0.14 | 0.14 | 0.13 | 0.13 | 0.12 | 0.12 | 0.11 | 0.10 | 0.09 |
| | 9 | 0.15 | 0.15 | 0.13 | 0.13 | 0.12 | 0.11 | 0.10 | 0.09 | 0.09 | 0.09 |
| | High | 0.13 | 0.12 | 0.11 | 0.11 | 0.11 | 0.10 | 0.10 | 0.10 | 0.09 | 0.09 |

Panel B: Double sorted value-weighted portfolio alphas

| Portfolios | SIZE | B/M | GP | ILLIQ | IVOL | $\beta^{MKT}$ |
|---|---|---|---|---|---|---|
| Low | 0.03 | -0.00 | -0.01 | 0.03 | 0.03 | -0.05 |
| | (0.35) | (-0.01) | (-0.20) | (0.35) | (0.40) | (-0.65) |
| 2 | -0.10 | -0.07 | -0.03 | -0.11 | -0.14 | -0.03 |
| | (-1.14) | (-0.83) | (-0.40) | (-1.33) | (-1.36) | (-0.35) |
| 3 | -0.05 | -0.02 | -0.02 | -0.01 | -0.07 | 0.01 |
| | (-0.45) | (-0.22) | (-0.26) | (-0.06) | (-0.77) | (0.13) |
| 4 | 0.04 | 0.06 | 0.10 | 0.01 | 0.02 | 0.01 |
| | (0.45) | (0.78) | (1.19) | (0.14) | (0.25) | (0.11) |
| 5 | 0.09 | -0.05 | -0.06 | -0.02 | 0.03 | 0.02 |
| | (0.96) | (-0.50) | (-0.67) | (-0.25) | (0.29) | (0.24) |
| 6 | 0.05 | -0.06 | -0.07 | -0.04 | 0.04 | -0.16 |
| | (0.51) | (-0.65) | (-0.74) | (-0.49) | (0.45) | (-1.72) |
| 7 | -0.19 | -0.03 | -0.05 | -0.02 | -0.03 | 0.07 |
| | (-1.89) | (-0.26) | (-0.41) | (-0.23) | (-0.33) | (0.47) |
| 8 | -0.01 | 0.12 | 0.18 | -0.05 | 0.15 | 0.08 |
| | (-0.14) | (0.85) | (1.21) | (-0.44) | (1.41) | (0.66) |
| 9 | 0.15 | 0.33 | 0.40 | 0.23 | 0.20 | 0.28 |
| | (0.86) | (1.97) | (2.28) | (1.80) | (1.56) | (1.98) |
| High | 0.35 | 0.31 | 0.28 | 0.58 | 0.37 | 0.33 |
| | (2.40) | (1.77) | (1.84) | (2.38) | (2.35) | (1.67) |
| High-Low | 0.32 | 0.31 | 0.29 | 0.55 | 0.34 | 0.38 |
| | (2.23) | (2.04) | (2.03) | (2.17) | (2.03) | (1.91) |

**Table 9: Performance estimates: emotion beta-based factor**

The table shows spanning tests of emotion beta factor (EMO) alphas employing 5 asset pricing models – Fama and French (2016, FF5), Hou, Xue, and Zhang (2015, *q*-factor), Hou, Mou, Xue, and Zhang (2019, *q*-factor$^+$), Barillas and Shanken (2018, BS6), and Daniel, Hirshleifer, and Sun (2020, DHS3). 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 ($\beta^{MEI}$) groups using the CRSP 20$^{th}$ and 80$^{th}$ percentile values of $\beta^{MEI}$. The intersections of the two size groups and the three $\beta^{MEI}$ groups generate six portfolios. The value-weighted EMO factor return is the average return of the two value-weighted high-$\beta^{MEI}$ portfolios minus the average return of the two value-weighted low-$\beta^{MEI}$ portfolios. We then run spanning tests and report alphas. FF5 includes market, size, book-to-market, profitability, and investment factors. *q*-factor comprises market, size, investment, and profitability factors; the *q*-factor$^+$ model includes the economic growth factor. BS6 incorporates market, size, value, investment, profitability, and momentum factors. Finally, DHS3 includes market, finance, and post earnings announcement drift factors. SMB* is Hou et al. (2015) size for *q*-factor and *q*-factor$^+$ model. HML* is Asness and Frazzini (2013) value factor in BS6 model. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is January 1995 to December 2018.

| | $\alpha$ | MKT | SMB* | HML* | RMW | CMA | IVA | ROE | EG | MOM | FIN | PEAD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| FF5 | 0.21 | 0.16 | 0.20 | -0.20 | -0.24 | -0.22 | | | | | | |
| | (2.25) | (5.68) | (5.48) | (-5.15) | (-6.05) | (-4.35) | | | | | | |
| *q*-factor | 0.25 | 0.13 | 0.20 | | | | -0.50 | -0.24 | | | | |
| | (2.21) | (3.93) | (6.37) | | | | (-9.59) | (-5.83) | | | | |
| *q*-factor$^+$ | 0.27 | 0.13 | 0.19 | | | | -0.49 | -0.23 | -0.03 | | | |
| | (2.22) | (3.77) | (5.91) | | | | (-9.52) | (-5.16) | (-0.42) | | | |
| BS6 | 0.27 | 0.15 | 0.20 | -0.27 | | | -0.23 | -0.26 | | -0.11 | | |
| | (2.69) | (5.28) | (5.35) | (-4.66) | | | (-3.53) | (-5.12) | | (-2.67) | | |
| DHS3 | 0.31 | 0.11 | | | | | | | | | -0.39 | 0.02 |
| | (2.66) | (3.62) | | | | | | | | | (-15.26) | (0.37) |

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

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

Model 1: $R^e_{t+1} = \alpha_{i,t} + \beta_{i,t}^{MEI^a} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{MOM} MOM_t + +\beta_{i,t}^{LIQ} LIQ_t + \varepsilon_{i,t},$

Model 2: $R^e_{t+1} = \alpha_{i,t} + \beta_{i,t}^{MEI^b} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{IVA} IVA_t + \beta_{i,t}^{ROE} ROE_t + \varepsilon_{i,t},$

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

Model 1 controls for the market (MKT), size (SMB), value (HML), momentum (MOM), and liquidity (LIQ) factors. Model 2 controls for Hou, Xue, and Zhang (2015) *q*-factors – the market (MKT), size (SMB), investment (IVA), and profitability (ROE). Finally, Model 3, controls for the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors. The models 1, 2, and 3 report the alphas ($\alpha_{FF5}$, $\alpha_q$, $\alpha_{BS6}$, and $\alpha_{DHS3}$) controlling for Fama and French (2015, FF5) 5-factors, Hou, Xue, Zhang (2015, *q*-factor) 4-factors, Barillas and Shanken (2018, BS6) 6-factors, and Daniel, Hirshleifer, and Sun (2020, DHS3) 3-factors for value-weighted portfolios. The last row presents the alpha differences between high and low portfolios. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| | Model 1 | | | | Model 2 | | | | Model 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolios | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ |
| Low | -0.06 | 0.04 | 0.01 | 0.07 | -0.03 | 0.03 | 0.00 | 0.05 | 0.02 | 0.09 | 0.07 | 0.13 |
| | (-0.71) | (0.48) | (0.19) | (0.90) | (-0.46) | (0.41) | (0.11) | (0.73) | (0.20) | (0.96) | (0.70) | (1.34) |
| 2 | 0.11 | 0.20 | 0.19 | 0.23 | 0.19 | 0.28 | 0.26 | 0.30 | 0.06 | 0.17 | 0.15 | 0.20 |
| | (1.27) | (2.09) | (2.25) | (2.59) | (1.96) | (2.71) | (2.68) | (2.84) | (0.73) | (1.86) | (1.79) | (2.05) |
| 3 | 0.08 | 0.16 | 0.14 | 0.19 | -0.05 | 0.04 | 0.02 | 0.13 | -0.04 | 0.03 | 0.02 | 0.07 |
| | (0.80) | (1.67) | (1.37) | (2.07) | (-0.50) | (0.50) | (0.34) | (1.61) | (-0.46) | (0.28) | (0.22) | (0.94) |
| 4 | -0.07 | -0.00 | -0.02 | 0.07 | -0.06 | -0.01 | -0.03 | 0.07 | 0.00 | 0.09 | 0.07 | 0.14 |
| | (-0.86) | (-0.03) | (-0.27) | (0.86) | (-0.76) | (-0.20) | (-0.49) | (0.92) | (0.01) | (0.97) | (0.84) | (1.68) |
| 5 | -0.08 | -0.02 | -0.03 | 0.05 | 0.03 | 0.08 | 0.07 | 0.17 | -0.02 | 0.02 | 0.00 | 0.09 |
| | (-0.81) | (-0.17) | (-0.36) | (0.50) | (0.32) | (0.90) | (0.85) | (1.90) | (-0.26) | (0.16) | (0.06) | (0.95) |
| 6 | -0.04 | 0.06 | 0.04 | 0.19 | -0.09 | -0.03 | -0.04 | 0.05 | -0.10 | -0.02 | -0.04 | 0.09 |
| | (-0.38) | (0.53) | (0.42) | (1.69) | (-0.95) | (-0.28) | (-0.46) | (0.43) | (-1.13) | (-0.25) | (-0.46) | (1.02) |
| 7 | 0.09 | 0.13 | 0.10 | 0.22 | -0.06 | -0.00 | -0.02 | 0.17 | 0.05 | 0.08 | 0.05 | 0.25 |
| | (0.81) | (1.04) | (0.79) | (2.01) | (-0.49) | (-0.01) | (-0.19) | (1.32) | (0.50) | (0.68) | (0.44) | (2.37) |
| 8 | -0.05 | -0.03 | -0.04 | 0.13 | 0.12 | 0.19 | 0.18 | 0.28 | -0.03 | 0.07 | 0.06 | 0.21 |
| | (-0.40) | (-0.21) | (-0.31) | (1.00) | (0.81) | (1.24) | (1.17) | (2.05) | (-0.21) | (0.50) | (0.43) | (1.63) |
| 9 | 0.02 | 0.32 | 0.32 | 0.43 | 0.13 | 0.26 | 0.25 | 0.40 | 0.18 | 0.32 | 0.32 | 0.40 |
| | (1.35) | (2.31) | (2.38) | (3.32) | (0.95) | (1.64) | (1.84) | (2.69) | (1.31) | (2.19) | (2.34) | (2.77) |
| High | 0.29 | 0.42 | 0.43 | 0.64 | 0.25 | 0.38 | 0.40 | 0.55 | 0.32 | 0.41 | 0.42 | 0.61 |
| | (1.89) | (2.44) | (2.52) | (3.38) | (1.81) | (2.46) | (2.61) | (3.22) | (2.23) | (2.41) | (2.49) | (3.64) |
| High – Low | 0.35 | 0.37 | 0.42 | 0.56 | 0.29 | 0.35 | 0.40 | 0.49 | 0.30 | 0.32 | 0.35 | 0.48 |
| | (2.31) | (2.03) | (2.50) | (3.11) | (2.03) | (1.98) | (2.53) | (2.78) | (2.29) | (1.85) | (2.35) | (2.92) |

**Table 11: Alpha estimates for emotion beta sorted portfolios: Robustness tests**

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

| | $\text{MEI}^{\perp}$ | | | | $\text{MEI}^{\perp\perp}$ | | | | $\text{MEI}^{\perp\perp\perp}$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolios | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ |
| Low | 0.01 | 0.09 | 0.07 | 0.13 | 0.03 | 0.11 | 0.09 | 0.16 | -0.07 | 0.00 | -0.02 | 0.04 |
| | (0.20) | (0.99) | (0.90) | (1.54) | (0.32) | (1.06) | (0.96) | (1.54) | (-0.80) | (0.04) | (-0.25) | (0.54) |
| 2 | -0.03 | 0.08 | 0.06 | 0.15 | -0.03 | 0.06 | 0.04 | 0.12 | 0.10 | 0.18 | 0.16 | 0.22 |
| | (-0.35) | (0.87) | (0.74) | (1.48) | (-0.38) | (0.62) | (0.50) | (1.33) | (1.13) | (1.92) | (1.72) | (2.25) |
| 3 | 0.00 | 0.06 | 0.05 | 0.11 | 0.00 | 0.09 | 0.07 | 0.12 | -0.05 | 0.04 | 0.02 | 0.10 |
| | (0.10) | (0.58) | (0.52) | (1.36) | (0.03) | (0.96) | (0.80) | (1.27) | (-0.49) | (0.37) | (0.20) | (1.04) |
| 4 | -0.06 | 0.01 | -0.00 | 0.08 | 0.00 | 0.09 | 0.07 | 0.15 | 0.07 | 0.14 | 0.13 | 0.19 |
| | (-0.61) | (0.16) | (-0.05) | (0.91) | (0.04) | (0.93) | (0.83) | (1.71) | (0.89) | (1.53) | (1.52) | (2.41) |
| 5 | 0.07 | 0.12 | 0.10 | 0.19 | -0.05 | 0.02 | 0.00 | 0.09 | -0.05 | 0.03 | 0.01 | 0.09 |
| | (0.69) | (1.15) | (1.01) | (1.97) | (-0.56) | (0.21) | (0.10) | (0.93) | (-0.51) | (0.26) | (0.11) | (0.90) |
| 6 | -0.01 | 0.07 | 0.06 | 0.15 | -0.04 | 0.04 | 0.02 | 0.14 | -0.06 | 0.00 | -0.01 | 0.11 |
| | (-0.09) | (0.62) | (0.55) | (1.50) | (-0.36) | (0.37) | (0.21) | (1.33) | (-0.58) | (0.06) | (-0.11) | (1.10) |
| 7 | 0.05 | 0.15 | 0.11 | 0.21 | 0.15 | 0.20 | 0.18 | 0.29 | 0.13 | 0.22 | 0.19 | 0.34 |
| | (0.45) | (1.37) | (1.11) | (1.98) | (1.33) | (1.60) | (1.46) | (2.51) | (1.00) | (1.42) | (1.48) | (2.55) |
| 8 | -0.03 | 0.09 | 0.08 | 0.28 | 0.05 | 0.17 | 0.14 | 0.36 | -0.05 | 0.06 | 0.04 | 0.22 |
| | (-0.21) | (0.60) | (0.57) | (1.80) | (0.34) | (1.10) | (1.09) | (2.22) | (-0.47) | (0.52) | (0.39) | (1.92) |
| 9 | 0.20 | 0.25 | 0.23 | 0.39 | 0.09 | 0.18 | 0.18 | 0.31 | 0.10 | 0.19 | 0.17 | 0.32 |
| | (1.49) | (1.72) | (1.57) | (2.71) | (0.73) | (1.30) | (1.18) | (2.36) | (0.66) | (1.27) | (1.13) | (2.18) |
| High | 0.34 | 0.43 | 0.44 | 0.55 | 0.39 | 0.42 | 0.43 | 0.59 | 0.44 | 0.48 | 0.48 | 0.63 |
| | (2.37) | (2.71) | (2.80) | (3.57) | (2.99) | (2.90) | (2.99) | (3.87) | (3.08) | (2.86) | (2.94) | (3.97) |
| High – Low | 0.33 | 0.34 | 0.37 | 0.42 | 0.36 | 0.31 | 0.34 | 0.43 | 0.51 | 0.47 | 0.50 | 0.59 |
| | (2.28) | (2.00) | (2.52) | (3.10) | (2.76) | (1.74) | (2.30) | (2.83) | (3.30) | (2.37) | (2.89) | (3.71) |

**Table 12: Alpha estimates for emotion beta sorted portfolios: Robustness tests**

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

Panel A: Emotion premium across different stock subsamples

| | S&P 500 | | | | Largest 1000 | | | | Liquid 1000 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Portfolios | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ |
| Low | -0.07 | 0.01 | 0.00 | 0.07 | 0.01 | 0.11 | 0.10 | 0.15 | -0.01 | 0.08 | 0.07 | 0.12 |
| | (-0.82) | (0.17) | (0.03) | (0.77) | (0.16) | (1.25) | (1.23) | (1.77) | (-0.17) | (0.92) | (0.84) | (1.39) |
| 2 | 0.01 | 0.08 | 0.06 | 0.15 | 0.01 | 0.07 | 0.06 | 0.14 | 0.03 | 0.11 | 0.10 | 0.17 |
| | (0.07) | (0.90) | (0.81) | (1.75) | (0.14) | (0.81) | (0.68) | (1.56) | (0.32) | (1.29) | (1.08) | (1.80) |
| 3 | -0.03 | 0.05 | 0.03 | 0.09 | -0.04 | 0.13 | 0.11 | 0.16 | -0.11 | -0.04 | -0.06 | -0.03 |
| | (-0.37) | (0.54) | (0.33) | (1.02) | (-0.31) | (1.08) | (1.01) | (1.49) | (-1.13) | (-0.42) | (-0.67) | (-0.27) |
| 4 | 0.11 | 0.19 | 0.18 | 0.24 | -0.03 | 0.05 | 0.03 | 0.08 | 0.00 | 0.09 | 0.07 | 0.12 |
| | (1.13) | (2.00) | (2.14) | (2.71) | (-0.35) | (0.48) | (0.35) | (0.86) | (0.05) | (0.87) | (0.81) | (1.20) |
| 5 | -0.02 | 0.06 | 0.04 | 0.17 | 0.09 | 0.17 | 0.15 | 0.26 | 0.04 | 0.12 | 0.11 | 0.19 |
| | (-0.23) | (0.65) | (0.47) | (2.00) | (0.99) | (1.70) | (1.65) | (2.93) | (0.43) | (1.35) | (1.27) | (2.09) |
| 6 | -0.05 | 0.05 | 0.03 | 0.13 | 0.03 | 0.11 | 0.10 | 0.18 | -0.00 | 0.08 | 0.07 | 0.17 |
| | (-0.55) | (0.50) | (0.33) | (1.44) | (0.34) | (1.13) | (1.01) | (2.03) | (-0.06) | (1.02) | (0.81) | (1.99) |
| 7 | -0.10 | -0.05 | -0.07 | 0.05 | 0.05 | 0.09 | 0.07 | 0.18 | 0.06 | 0.10 | 0.09 | 0.17 |
| | (-0.97) | (-0.42) | (-0.67) | (0.50) | (0.45) | (0.88) | (0.73) | (1.83) | (0.57) | (0.89) | (0.80) | (1.61) |
| 8 | 0.13 | 0.18 | 0.16 | 0.34 | 0.03 | 0.09 | 0.07 | 0.20 | -0.03 | 0.03 | 0.00 | 0.15 |
| | (1.03) | (1.45) | (1.21) | (2.84) | (0.26) | (0.82) | (0.62) | (1.76) | (-0.27) | (0.22) | (0.08) | (1.32) |
| 9 | 0.06 | 0.16 | 0.16 | 0.28 | 0.27 | 0.34 | 0.34 | 0.45 | 0.21 | 0.29 | 0.28 | 0.44 |
| | (0.48) | (1.17) | (1.10) | (1.81) | (1.81) | (2.28) | (2.31) | (2.79) | (1.52) | (1.84) | (1.88) | (2.54) |
| High | 0.46 | 0.53 | 0.53 | 0.70 | 0.55 | 0.65 | 0.66 | 0.78 | 0.45 | 0.52 | 0.52 | 0.59 |
| | (3.32) | (3.25) | (3.25) | (4.23) | (4.05) | (3.91) | (4.04) | (4.67) | (3.33) | (3.55) | (3.68) | (4.09) |
| High – Low | 0.53 | 0.52 | 0.53 | 0.63 | 0.54 | 0.53 | 0.55 | 0.62 | 0.48 | 0.44 | 0.45 | 0.47 |
| | (3.93) | (2.85) | (3.34) | (4.12) | (4.32) | (3.06) | (3.73) | (4.33) | (3.40) | (2.58) | (3.16) | (3.73) |

Panel B: Subperiod analysis

| | Economic condition | | | | | | | | Sentiment | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Non-crisis | | | | Crisis | | | | Low | | | | High | | | |
| Portfolios | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ | $\alpha_{FF5}$ | $\alpha_q$ | $\alpha_{BS6}$ | $\alpha_{DHS3}$ |
| Low | -0.12 | -0.04 | -0.08 | -0.06 | 0.15 | 0.26 | 0.22 | 0.34 | 0.03 | 0.06 | -0.02 | 0.17 | -0.10 | 0.08 | 0.10 | 0.07 |
| | (-1.25) | (-0.47) | (-0.90) | (-0.70) | (0.96) | (1.56) | (1.64) | (2.28) | (0.28) | (0.46) | (-0.15) | (1.12) | (-0.88) | (0.58) | (0.89) | (0.50) |
| 2 | 0.09 | 0.12 | 0.05 | 0.19 | -0.14 | 0.04 | -0.02 | 0.09 | 0.07 | 0.09 | 0.03 | 0.17 | -0.07 | 0.03 | 0.07 | 0.11 |
| | (1.06) | (1.26) | (0.75) | (2.18) | (-0.80) | (0.22) | (-0.15) | (0.67) | (0.50) | (0.71) | (0.30) | (1.39) | (-0.68) | (0.30) | (0.63) | (1.03) |
| 3 | -0.06 | -0.00 | -0.06 | 0.04 | 0.07 | 0.26 | 0.22 | 0.19 | 0.11 | 0.13 | 0.07 | 0.18 | -0.20 | -0.03 | 0.00 | 0.00 |
| | (-0.56) | (-0.06) | (-0.63) | (0.44) | (0.34) | (1.15) | (1.12) | (0.95) | (0.87) | (0.99) | (0.59) | (1.34) | (-1.82) | (-0.21) | (0.08) | (0.08) |
| 4 | 0.07 | 0.12 | 0.06 | 0.16 | 0.09 | 0.24 | 0.20 | 0.25 | 0.11 | 0.17 | 0.10 | 0.20 | 0.05 | 0.07 | 0.10 | 0.16 |
| | (0.64) | (1.15) | (0.67) | (1.52) | (0.48) | (1.08) | (1.06) | (1.55) | (0.85) | (1.31) | (0.78) | (1.49) | (-0.45) | (0.56) | (0.87) | (1.25) |
| 5 | -0.11 | -0.09 | -0.12 | -0.03 | 0.12 | 0.30 | 0.27 | 0.36 | 0.12 | 0.15 | 0.12 | 0.17 | -0.22 | -0.12 | -0.12 | 0.08 |
| | (-1.05) | (-0.85) | (-1.11) | (-0.29) | (0.75) | (2.14) | (1.99) | (2.78) | (1.17) | (1.49) | (1.23) | (1.69) | (-2.44) | (-0.97) | (-1.13) | (0.67) |
| 6 | -0.02 | 0.06 | -0.00 | 0.09 | -0.03 | 0.20 | 0.16 | 0.21 | 0.09 | 0.15 | 0.10 | 0.23 | -0.16 | 0.01 | 0.04 | 0.09 |
| | (-0.26) | (0.61) | (-0.02) | (0.91) | (-0.15) | (1.18) | (0.93) | (1.28) | (0.66) | (1.10) | (0.82) | (1.51) | (-1.39) | (0.09) | (0.31) | (0.78) |
| 7 | -0.04 | -0.01 | -0.06 | -0.01 | 0.33 | 0.43 | 0.40 | 0.47 | 0.12 | 0.13 | 0.10 | 0.14 | -0.07 | 0.01 | 0.03 | 0.21 |
| | (-0.35) | (-0.07) | (-0.59) | (-0.12) | (1.69) | (2.34) | (2.33) | (2.57) | (0.98) | (1.06) | (0.79) | (1.23) | (-0.41) | (0.06) | (0.19) | (1.13) |
| 8 | -0.15 | -0.03 | -0.09 | -0.00 | 0.40 | 0.46 | 0.46 | 0.68 | 0.21 | 0.23 | 0.18 | 0.36 | -0.21 | -0.10 | 0.09 | 0.13 |
| | (-1.16) | (-0.32) | (-0.81) | (-0.01) | (1.69) | (1.87) | (1.89) | (2.86) | (1.69) | (1.81) | (1.32) | (2.44) | (-1.13) | (-0.49) | (0.54) | (0.67) |
| 9 | -0.01 | 0.00 | -0.02 | 0.06 | 0.40 | 0.53 | 0.50 | 0.71 | 0.17 | 0.25 | 0.19 | 0.24 | 0.12 | 0.19 | 0.19 | 0.42 |
| | (-0.09) | (0.04) | (-0.17) | (0.50) | (1.30) | (2.04) | (1.84) | (2.29) | (0.69) | (0.99) | (0.82) | (0.81) | (0.59) | (0.87) | (0.88) | (1.68) |
| High | 0.32 | 0.36 | 0.36 | 0.35 | 0.84 | 1.03 | 0.98 | 1.30 | 0.37 | 0.45 | 0.49 | 0.54 | 0.63 | 0.73 | 0.72 | 0.92 |
| | (2.40) | (2.60) | (2.53) | (2.58) | (3.05) | (3.99) | (3.68) | (4.96) | (1.82) | (2.00) | (2.24) | (2.46) | (3.07) | (3.03) | (3.10) | (3.81) |
| High – Low | 0.44 | 0.40 | 0.44 | 0.41 | 0.69 | 0.76 | 0.76 | 0.96 | 0.33 | 0.39 | 0.51 | 0.37 | 0.73 | 0.65 | 0.62 | 0.85 |
| | (3.23) | (2.67) | (2.89) | (2.98) | (2.83) | (2.51) | (2.93) | (4.42) | (2.49) | (2.02) | (3.25) | (2.39) | (3.56) | (2.91) | (2.87) | (3.71) |

# Appendix A

**Table A1: Summary statistics: Newspaper dataset**

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

The table presents correlation between conditional emotion, mood, sentiment, uncertainty, and tone betas. The emotion beta ($\beta^{MEI}$) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and a set of factors listed in equation (2). Then, we take the absolute value of $\beta^{MEI}$. The mood beta ($\beta^{Mood}$) of Hirshleifer 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. 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 ($\beta^{SENT}$) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index and a set of factors listed in equation (2). We generate the consumer confidence beta ($\beta^{UMCCI}$) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and a set of factors listed in equation (2). Following Bali et al. (2017), we compute the uncertainty beta ($\beta^{UNC}$) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta ($\beta^{EPU}$) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and a set of factors listed in equation (2). We derive two tone betas ($\beta^{LM}$ and $\beta^{HN}$) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and a set of factors listed in equation (2). The LM and HN tones are the ratio of difference between positive and negative word counts to the total of positive and negative word counts using Loughran and McDonald (2011) and Henry (2008) positive and negative word dictionaries respectively. The estimation period is from January 1995 to December 2018.

| | $\beta^{MEI}$ | $\beta^{Mood}$ | $\beta^{SENT}$ | $\beta^{UMCCI}$ | $\beta^{UNC}$ | $\beta^{EPU}$ | $\beta^{LM}$ | $\beta^{HN}$ |
|---|---|---|---|---|---|---|---|---|
| $\beta^{MEI}$ | 1 | | | | | | | |
| $\beta^{Mood}$ | 0.238 | 1 | | | | | | |
| $\beta^{SENT}$ | 0.019 | -0.019 | 1 | | | | | |
| $\beta^{UMCCI}$ | 0.040 | -0.024 | 0.189 | 1 | | | | |
| $\beta^{UNC}$ | 0.050 | 0.007 | 0.093 | -0.252 | 1 | | | |
| $\beta^{EPU}$ | 0.012 | -0.024 | 0.016 | -0.469 | 0.373 | 1 | | |
| $\beta^{LM}$ | -0.011 | 0.109 | -0.204 | 0.399 | -0.429 | -0.535 | 1 | |
| $\beta^{HN}$ | -0.011 | 0.028 | -0.081 | 0.521 | -0.429 | -0.629 | 0.822 | 1 |

**Table A3: Fama-MacBeth cross-sectional regression estimates**

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion beta ($\beta^{MEI}$), valence-based emotion beta ($\beta^{Valence}$) and a set of lagged control variables using the Fama-MacBeth method. The control variables are market beta ($\beta^{MKT}$), volatility beta ($\beta^{VIX}$), market capitalization (SIZE), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). Panel B presents the results from regressing monthly excess returns in two- to 6-months ahead against $\beta^{MEI}$ after controlling for all other predictive variables and for brevity, we do not report their intercepts, and coefficients. All results are microcap adjusted. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported below the estimates. The estimation period is from January 1995 to December 2018.

| | Without industry effects | | | | With industry effects | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\beta^{MEI}$ | 1.38 | 1.09 | 0.84 | 0.56 | 0.99 | 0.84 | 0.58 | 0.42 |
| | (2.54) | (3.31) | (3.25) | (2.52) | (2.55) | (2.91) | (2.56) | (2.02) |
| $\beta^{Valence}$ | -0.08 | -0.17 | -0.10 | -0.23 | -0.02 | -0.08 | -0.09 | -0.20 |
| | (-0.37) | (-0.95) | (-0.59) | (-1.35) | (-0.12) | (-0.48) | (-0.59) | (-1.36) |
| $\beta^{MKT}$ | | 0.31 | 0.24 | 0.29 | | 0.26 | 0.18 | 0.26 |
| | | (1.35) | (1.23) | (1.67) | | (1.33) | (1.05) | (1.70) |
| $\beta^{VIX}$ | | -0.46 | -0.55 | -0.40 | | -0.34 | -0.45 | -0.34 |
| | | (-1.69) | (-2.06) | (-1.47) | | (-1.54) | (-2.08) | (-1.51) |
| SIZE | | | -0.29 | -0.21 | | | -0.25 | -0.20 |
| | | | (-4.05) | (-3.28) | | | (-3.88) | (-3.29) |
| B/M | | | 0.44 | 0.48 | | | 0.58 | 0.59 |
| | | | (4.24) | (4.42) | | | (6.33) | (6.14) |
| MOM | | | 0.04 | -0.13 | | | 0.02 | -0.13 |
| | | | (0.21) | (-0.67) | | | (0.15) | (-0.76) |
| REV | | | | -1.09 | | | | -1.25 |
| | | | | (-2.07) | | | | (-2.59) |
| I/A | | | | 0.21 | | | | 0.17 |
| | | | | (1.72) | | | | (1.56) |
| ROE | | | | 0.69 | | | | 0.78 |
| | | | | (2.72) | | | | (3.42) |
| ILLIQ | | | | 0.29 | | | | 0.30 |
| | | | | (6.76) | | | | (6.63) |
| IVOL | | | | 0.56 | | | | 0.54 |
| | | | | (7.08) | | | | (7.61) |
| MAX | | | | -0.21 | | | | -0.22 |
| | | | | (-3.49) | | | | (-3.98) |
| Intercept | 1.08 | 0.80 | 0.71 | 0.25 | 0.87 | 0.75 | 0.53 | -0.03 |
| | (4.12) | (3.28) | (2.88) | (1.00) | (2.63) | (2.87) | (1.76) | (-0.10) |
| Adj. R-squared | 0.86% | 4.10% | 5.82% | 7.94% | 6.61% | 8.39% | 10.88% | 11.34% |
| N months | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 |

**Table A4: Ten most frequent emotional and tonal words**

The table presents 10 most frequent emotional and tonal words. We compute excitement and anxiety word counts using Taffler et al.'s (2021) 'excitement' and 'anxiety' keyword dictionaries. positive and negative word counts are based on Loughran and McDonald (2011) positive and negative dictionaries. The words are counted using articles from 21 newspapers (see Table A1 for the list of newspapers) from January 1990 to 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 A5: Proportion of articles across MEI and tone scores**

The table reports the percentages of articles across quintiles of market emotion index and tone over the sample period. The market emotion index is the total of excitement and anxiety word counts to the total words in a month. We compute excitement and anxiety word counts using Taffler et al.'s (2021) 'excitement' and 'anxiety' keyword dictionaries. Tone is the ratio of difference between positive and negative word counts to the total of positive and negative word counts based on Loughran and McDonald (2011) positive and negative dictionaries. The sample period is from 1990 to 2018.

| | | | Market Emotion Index | | | | |
|---|---|---|---|---|---|---|---|
| | Quintile | | 1 | 2 | 3 | 4 | 5 |
| | | Scores | 0.013 | 0.027 | 0.039 | 0.051 | 0.077 |
| Tone | 1 | -0.872 | **0.065** | 0.040 | 0.034 | 0.032 | 0.030 |
| | 2 | -0.582 | 0.034 | **0.041** | 0.043 | 0.041 | 0.041 |
| | 3 | -0.357 | 0.031 | 0.042 | **0.044** | 0.043 | 0.046 |
| | 4 | -0.108 | 0.031 | 0.040 | 0.044 | **0.046** | 0.047 |
| | 5 | 0.279 | 0.033 | 0.038 | 0.037 | 0.040 | **0.037** |

# Appendix B

*Case Study 1*

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

A Rally That Needs More 'E'

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

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

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

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

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

But long-term history also offers an important clue.

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

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

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

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

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

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

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

When will the earnings outlook turn around?

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

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

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

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

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

Score: MEI 0.09 and LM 0.00

*Case Study 2*

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

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

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

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

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

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

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

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

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

In major U.S. market action:

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

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

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

Score: MEI 0.08 and LM 0.00

# Appendix C

### C1. Summary of the keyword dictionary development process

Taffler et al. (2021) build their emotion keyword dictionaries by analyzing U.S. media reports from a range of sources during the internet bubble because of a highly charged and wide range investor emotions manifest during this period. They then validate their keyword dictionaries in the run-up to, and during, the Global Financial Crisis. The initial stage in their dictionary development was an analysis of media reports published in widely-circulated U.S. newspapers from October 1998 to September 2002. The resulting emotion word list was then supplemented using Harvard IV-4 GI and Lasswell Value dictionaries, and further enriched by important human emotion words from the *Book of Human Emotions* (Watt-Smith, 2015). Keyword-in-context (KWIC) was employed to ensure all emotions words used had direct market relevant emotional content. All retained emotion words were then classified using a rigorous and systematic process to one of the seven emotion lexicons based on an initial classification by each of the three authors separately and then with any disagreement resolved by discussion and reference back to the KWIC. Additional details about the dictionary construction process are available in Taffler et al. (2021).

**C2. Keywords: Emotion dictionaries are available on request.**