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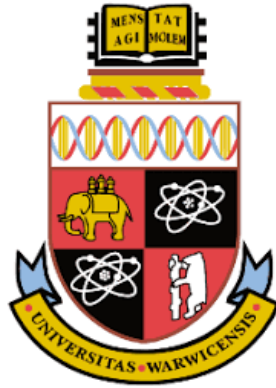
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Investor Emotions and Asset Prices

by

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Thesis

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—Paulo Coelho; *The Alchemist* (1993)

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I dedicate this thesis to my family.

Declarations

I declare the following:

- This thesis has not been submitted for a degree to any other university.
- Chapter 2, entitled “Anxiety, Excitement, and Asset Prices”, is co-authored with Professor Alok Kumar and Professor Richard J. Taffler.
- Chapter 3, entitled “Emotional Exuberance and Local Return Predictability”, is co-authored with Professor Alok Kumar and Professor Richard J. Taffler.
- Chapter 4, entitled “An Emotion-imbued Behavioral Factor Model”, principally sole authored.

Mohammad Shehub Bin Hasan

September 2021

Abstract

This thesis explores how variations in investor emotions influence their portfolio decisions and consequently affect asset prices. Broadly, emotions can be either ‘integral’ or ‘incidental’. Integral emotions such as excitement and anxiety enter into investor decision-making processes directly and are fundamental in nature. In contrast, incidental emotions such as weather-induced mood, sports sentiment, or music are indirect, more short-lived, and less powerful. The finance literature principally focuses on the relationship between incidental emotions and market returns. This creates a lacuna to explore the influence of integral emotions on asset prices. My thesis attempts to bridge this research gap and contributes by investigating the impact of integral emotions, such as their states of excitement and anxiety, on investor decision-making and asset prices in real world rather than experimental markets.

In my three empirical chapters, I show how investors’ emotional attachments to stocks are priced in the cross-section of stock returns, can predict local stock returns, and explain a broad range of asset pricing anomalies when included in a factor model.

In Chapter 2, I develop a novel market emotion index focusing on investors’ integral emotions, in particular excitement and anxiety. I measure stock-specific emotion sensitivity – *emotion beta* – to changes in the market emotion index, which measures the ‘emotional utility’ stocks have for investors. Drawing on the psychology literature, I demonstrate that investors derive high emotional utility from stocks that have ‘emotional glitter’ compared to stocks with low emotional utility. This, I show, contributes to short-term mispricing and creates return predictability in the broad cross-section of U.S. stocks. A Long-Short emotion-based trading strategy generates an alpha of 4.92%. This mispricing ameliorates in about four months. This return predictability mechanism is distinct and incremental to the effects of mood, sentiment, uncertainty, and narrative tone. Collectively, I demonstrate that integral investor emotions play a key role in investors’ portfolio decisions leading to return predictability.

If investors develop ‘love’/‘hate’ relationships with their stocks as I find in Chapter 2, then obviously these relationships will be stronger for stocks with which investors are familiar. The body of literature on geography and stocks returns shows that investors prefer domestic to foreign, and state to out-of-state stocks. In Chapter 3, I draw on this strand of literature along

with psychology and show that investors' 'emotional exuberance' about the state of the stock market as reflected in the local media helps predict local stock returns. This local return predictability differs to the effects of local economic conditions, sentiment, local optimism, and local bias. I demonstrate local investors' emotional exuberance, as measured by their level of excitement minus anxiety, creates mispricing in a geographic segment of the stock market. An emotion-driven geography-based Long-Short trading strategy earns an annualized alpha of 9.17%. Arbitrage forces of nonlocals take about six months to completely absorb the emotion-driven local mispricing I identify. Specifically, in chapter 3, I focus on local investor emotional dynamics and examine its ability to influence their portfolio decisions and future local stock returns.

In Chapters 2 and 3, I establish investor emotions are an important determinant of asset prices. Thus, asset pricing models should consider these as a tradable pricing factor helping to explain a broad range of asset pricing anomalies. Hence, finally, in Chapter 4, I introduce investors' emotional relationships with the stocks they invest in, as measured by their emotional utility, directly as a priced factor and include this in an asset pricing model. This emotion factor generates an average excess return of 0.39% per month with a *t*-statistic of 3.34. Specifically, I propose a 4-factor 'market-behavioral-emotional' composite model and show this is able to explain most traditional and recently proposed asset pricing model factors. Conversely, none of the existing factor models can account for this investor emotion-based factor suggesting it is capturing something distinct. In parallel, my newly proposed emotion-imbued behavioral factor model explains most of the robust asset pricing anomalies reported in the literature.

Considering my three main chapters together, I believe my thesis makes an important and original contribution to the asset pricing and investor psychology literature by empirically demonstrating the impact of investors' integral emotions on their decision-making in complex real-world settings as opposed to more narrowly-based laboratory studies.

Chapter 1

Introduction

Emotions predictably and pervasively influence judgement and decision making (Lerner et al., 2015). Intensified emotions can have long-lasting and ever-increasing influence on behavior (Loewenstein and Lerner, 2003), and can have considerable predictive power in driving ultimate decision-making. Importantly, decisions made under the influence of particularly nonconscious emotions are different from those predicted by rational models as such emotions can propel behavior in a direction that is different from those made only considering costs and benefits (Loewenstein, 2000). This is because apart from seeking to maximizing the utility of wealth, individuals want to maximize their psychic expected utility (see, for example, Caplin and Leahy, 2001). Collectively, emotions both conscious and more powerfully nonconscious, should have important asset pricing implications through their influence on investor behavior and decision making.

The finance literature has started to explore the relationship between emotions and market pricing and economic outcomes from two perspectives. First, it seeks to shed light on the role various incidental emotions, i.e., emotions not related to the decision at hand, play. These emotions take the form of weather-related mood (Saunders, 1993; Kamstra, Kramer, and Levi, 2000; Hirshleifer and Shumway, 2003; Chhaocharia et al., 2019; Chhaocharia, Korniotis, and Kumar, 2020), sports sentiment (Edmans, Garcia, and Norli, 2007), narrative and photo pessimism (Tetlock, 2007; Obaid and Pukthuanthong, 2021), mood-induced seasonality (Hirshleifer, Jiang, and DiGiovanni, 2020), and music sentiment (Edmans et al., 2021). A second set of studies work with emotions in a laboratory setting and show experimentally that emotions drive decision-making in abstract settings whether they are caused by exogenous factors or induced by outcomes of past choices (Kuhnen and Knutson, 2011). Excited traders and investors spur stock market bubbles in the laboratory (Andrade, Odean, and Lin, 2016), and anxiety-induced fear depresses market prices (Breaban and Noussair, 2018). However, there is little or no evidence showing the direct influence of emotions on investor decision-making in real-world stock market settings which is the research gap this thesis addresses.

In fact, both strands of literature do not meet and, importantly, neither examines the influence of integral emotions, i.e., often nonconscious emotions related to decisions at hand, in a real-world setting. My thesis builds on these recent developments and presents new evidence showing how investor integral emotions of excitement and anxiety (and other integral emotions indirectly) affect their investment decision-making and consequently asset prices.

I begin by exploring whether anxiety and excitement influence investor decision making and lead to return predictability. The asset pricing literature shows that mood is significantly correlated with stock returns. Stocks with higher sensitivities to aggregate mood earn higher return during rising mood periods and earn lower returns as mood goes down (Hirshleifer et al., 2020). As indirect incidental mood affects stock returns, then it is likely that investors' direct and much more powerful, as more fundamental and often nonconscious, integral emotions will have more significant and longer lasting impact on future stock returns.

In Chapter 2, I examine the impact of integral emotions on portfolio decisions and asset prices. I draw on the emotions in decision making literature and psychological object relations theory, and show that investors enter into emotional relationships with their stocks and derive psychological utility, which I term as '*emotional utility*', from their investments. My main conjecture is that stocks with high emotional utility will attract investors because of their emotional glitter and that will dominate stocks in investment portfolios with low emotional utility. I speculate this phenomenon creates price pressure leading to higher future stock returns.

Using a new dictionary of anxiety- and excitement-related keywords, I measure the emotional state of the market and compute firm-level sensitivity to changes in market-level emotions (i.e., emotion beta). I find that stocks with high emotion betas outperform low emotion beta stocks, and this performance differential is corrected in about four 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 generates an alpha of 4.92%. This evidence of emotion-based predictability is distinct from the known pricing effects of mood, sentiment, economic and policy uncertainty, and tone. Collectively, my findings show that emotional connections between investors and firms are priced.

In Chapter 3, I extend my investigation into local stocks mainly because investors are most likely to engage emotionally more with local compared to nonlocal stocks. The

geography-based return predictability literature shows that local investors prefer local stocks for familiarity reasons known as ‘local bias’ (e.g., Coval and Moskowitz, 1999; Huberman, 2001; Hong, Kubik, and Stein, 2008). I speculate local investor emotional exuberance about the state of the stock market in addition to simple local bias drives local portfolio choices. If this is so then it is likely that when local investor excitement about the stock market dominates their anxiety, they will invest more in local stocks creating price pressure, and the converse when anxiety dominates excitement, leading to local stock return predictability.

Specifically, I explore how local investor integral emotions of excitement and anxiety about the stock market influence their decision-making and consequently lead to predictable patterns in local stock returns. Reflecting this, I show an investor emotion-driven geography-based trading strategy generates an annualized alpha of 9.17% during the 1990 to 2018 period. This mispricing continues for up to six months. Local investor emotions have a stronger impact on return predictability in states where residents are more educated, have a lower minority population, and enjoy higher levels of income. Local emotion-based predictability differs from the known effects of narrative tone, sentiment, local optimism, local macroeconomic news, and local bias. Further, such predictability remains significant when I exclude large states, oil-producing and consuming states, and states with large dominant firms. Collectively, my findings demonstrate that local investors obtain additional emotional utility from investing in local stocks, and this is an important determinant of local asset prices.

My findings, so far, demonstrate the power of investor emotions in predicting future stock returns and mispricing both in the cross-section and with local stocks. I also establish that the influence of integral investor emotions is incremental and distinct to incidental feelings, return predictors, and firm characteristics. The uniqueness and importance of this discovery leads to the natural extension of including investor emotions in a factor model, *inter alia*, to examine whether prominent asset pricing model factors can explain a factor measuring investor integral emotions or whether such a factor is distinct. In parallel, it is obvious to wonder whether such an investor emotions-based factor can help explain robust asset pricing anomalies. Factor models, such as the CAPM (Sharpe, 1964; Lintner, 1965; Black, 1972), Fama and French three- and five-factor model (Fama and French, 1993, 2015), the *q*-factor model (Hou, Xue, and Zhang, 2015), the mispricing-factor model (Stambaugh and Yuan, 2017), the six-factor model (Barillas and Shanken, 2018), and the behavioral three-factor model of Daniel, Hirshleifer, and Sun (2020) help explain the cross-section of expected stock returns.

However, none of the models include a factor related to investor emotions. Daniel, Hirshleifer, and Sun's (2020) behavioral factor model includes two behavioral biases – overconfidence and inattention – investors are prone to. However, these biases are different from investor *emotions* and integral emotions are more powerful and at sufficient levels of intensity are very difficult to detach from decision making (see, for example, Rozin, Millman, and Nemeroff, 1986; Loewenstein, 1996).

In Chapter 4, I propose an emotion-imbued behavioral factor model as assets have both economic and emotional utility for investors. I directly measure the degree of emotional attachment investors have for stocks and introduce this as a priced factor into a behavioral asset pricing model. My emotion factor is motivated by investors' integral emotions and their psychological relationships with the assets they invest in. I show that my emotion-imbued behavioral factor model largely subsumes traditional factor models. Specifically, I augment the recent Daniel, Hirshleifer, and Sun (2020, DHS) three-factor model – the market and two behavioral factors – with an investor emotion factor. This 4-factor market-behavioral-emotional model enhances the DHS behavioral model and outperforms other factor models in explaining a broad range of return anomalies. I conclude that stock emotional utility complements risk-based and behavioral factors in explaining asset returns.

Overall, my thesis makes an original contribution by demonstrating the role of investors' integral emotions on asset prices. In particular, I show how investor emotions, such as excitement and anxiety, shape their emotional relationships with the stocks they invest in and derive emotional utility from. Through this thesis, I highlight a return predictability mechanism that is incremental to known pricing effects. My thesis, thus, contributes to the return predictability literature. I also show that investor emotions help predict local stock returns and such predictability is distinct from local economic conditions, local sentiment, and local bias. Finally, I show that it is important to recognize that investor integral emotions are priced if we want to understand more fully the determinants of the cross-section of stock returns and explain market anomalies. Taken together, my thesis contributes by providing novel insights in understanding the role played by fundamental emotions, both conscious and most importantly, nonconscious, in investor decision making, outside of the laboratory in a real-world setting, and associated asset pricing implications.

Chapter 2

Anxiety, Excitement, and Asset Prices¹

2.1 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. This continuing struggle between excitement and anxiety suggests that investment activity can generate mixed feelings that may 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 may be prone to emotional conflict as many of the investment decisions they make can be affected by their emotions (Kuhnen and Knutson, 2011; Tuckett and Taffler, 2012), even if they do not acknowledge this directly (Taffler, Spence, and Eshraghi, 2017).

The role of emotions in decision-making is a dominant theme in the psychology literature.² 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

¹ This chapter is based on a research paper jointly authored with Alok Kumar and Richard Taffler. The paper has been presented at the European Financial Management Association 2021, and Warwick University Finance Brown Bag Seminar.

² Consistent with the psychology literature, we use the terms ‘emotion’, ‘affect’, and ‘feeling’ interchangeably to convey subjective experience (Auchincloss and Samberg, 2012).

DiGiovanni, 2020; Obaid and Pukthuanthong, 2021; Edmans et al., 2021).³ 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 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, to measure an individual stock's emotional utility to investors, we first construct a market-level emotion index. 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.⁴ For each month during the January 1990 to December 2018 sample period, we use the ratio of difference between excitement and anxiety word counts in newspaper articles to the total number of excitement and anxiety words to derive the market

³ *Incidental* emotions are induced by exogenous factors that are unrelated to the current decision (e.g., weather), while *integral* emotions are endogenous as they are generated by considerations of the current decision task itself (e.g., excitement (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.

⁴ 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).

emotion index. This 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 the 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 charge rather than its valence.⁵ 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 quintile 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

⁵ 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, the excess buying pressure could generate higher returns in the near future.

2018 sample period, the high-minus-low portfolio earns an abnormal return of 0.41% per month (t -statistic = 5.23) on a risk-adjusted basis. Similarly, the characteristic-adjusted average excess return is 0.54% per month (t -statistic = 3.80). 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 four months and then becomes insignificant. This evidence indicates that the alpha estimates of emotion beta portfolios capture the mispricing of stocks with high emotional sensitivity, which eventually gets corrected over the next few months.

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 0.55 with t -statistic of 4.06. In economic terms, this estimate implies that a one standard deviation shift in conditional emotion beta is associated with a $0.55 \times 2.43 = 1.34\%$ shift in stock return in the 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, 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, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and Bali, Brown, and Tang's (2017) economic uncertainty index 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 follow Ball et al. (2020) to control for low market capitalization firms (i.e., microcaps) and find similar results. 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 find similar results when we construct

several variants of the market emotion index. And 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, Russell, and Peterson, 2005; Posner et al., 2009),⁶ we find that it is the emotional intensity of investor engagement with a stock that is priced rather than simply its positive/negative valence.⁷

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 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

⁶ The affective circumplex model of neurophysiological processing of emotions focuses on two dimensions: valence (pleasant/unpleasant) and arousal (activation/deactivation). Arousal increases with the intensity of both positive and negative valence. The combination of these two factors determines how individuals experience and refine emotional states.

⁷ 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.

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 the 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.

2.2 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).⁸

We introduce the concept of emotional utility and posit that investors enter into emotionally-charged relationships with the stocks they invest in. Investors are likely to experience different emotions such as excitement and anxiety and enter into ambivalent object-relationships with stocks of a ‘love’ and ‘hate’ nature affecting 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 that investors are attracted to stocks that have emotional ‘glitter’, i.e., high emotional utility.

⁸ In contrast, incidental emotions are less decision context specific (Watson and Tellegen, 1985), and tend to be short-lived.

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:

***Hypothesis 1:** Emotion beta, which measures an asset's return sensitivity to the market emotion index, will be positively associated with future stock returns.*

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:

***Hypothesis 2:** 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:

***Hypothesis 3:** Anxiety- and excitement-based return predictability is distinct from return predictability identified using mood, sentiment, and uncertainty measures.*

2.3 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.

2.3.1 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 2.A.1 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.

2.3.2 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 et al. (2021), we categorize emotional word mentions in our news articles in different ways. These lexicons

were originally constructed to capture the different powerful investor emotions manifest during the highly emotionally-charged dot.com bubble period.

Taffler et al. (2021) who 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. Appendix 2.A.1 summarizes their lexicon construction method.⁹ 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 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. We also perform a principal component analysis (PCA) of the word counts of the seven Taffler et al. (2021) emotion keyword lexicons and find these collapses into two factors. Excitement relates to the first factor, and anxiety mostly explains the second factor.¹⁰

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

⁹ 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.

¹⁰ When we measure our market emotion index using the factors derived by principal component analysis, i.e., $MEI_{F,t} = \frac{Factor_1 - Factor_2}{Factor_1 + Factor_2}$, we find qualitatively similar results.

the two Taffler et al. (2021) keyword lexicons of excitement and anxiety.¹¹ We follow Henry and Leone (2016) and generate our market emotion index (*MEI*) measure as:

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

where $Excitement_t$ and $Anxiety_t$ are the respective excitement and anxiety word counts derived from news articles in month t relative to the total number of words across the articles. Individual words receive equal weights.¹²

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.

2.3.3 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

¹¹ In unreported tests, we also construct two variations of our market emotion index, including all the seven emotion categories developed by Taffler et al. (2021). First, we take the difference between Excitement-related and Anxiety-related word counts in month t and scale the difference by total words in that month, $MEI_{Net,t} = \frac{(Excitement_t + Mania_t) - (Anxiety_t + Blame_t + Denial_t + Guilt_t + Panic_t)}{Total\ Words_t}$. Second, we sum all the emotional word mentions and scale it by total words, $MEI_{Total,t} = \frac{Excitement_t + Anxiety_t + Blame_t + Denial_t + Guilt_t + Mania_t + Panic_t}{Total\ Words_t}$. In both cases, we find qualitatively similar results.

¹² 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.

(2010) who show how the media reflects people's anxiety associated with aviation disasters, which affects asset prices.

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 equivalent measure using their dictionaries is 0.72 (p -value 0.00).¹³ This provides initial evidence that we are capturing investor emotions. Our emotions-based measure also differs from established sentiment measures. In fact, our market emotion index has correlations of only 0.05 (p -value = 0.31) and -0.02 (p -value = 0.69), respectively, with the Baker and Wurgler (2006) and Jiang et al. (2019) sentiment indices.

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 'boosted' from our excitement keyword dictionary.^{14,15} In both cases, the resulting market emotion indices correlate at 0.99 with our main market emotion index.

¹³ 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.

¹⁴ Baker, Bloom, and Davis (2016) also use the terms 'uncertain' and 'uncertainty' to develop their economic policy uncertainty (EPU) index.

¹⁵ We additionally remove 'shrink', 'shrinks', 'shrinking', 'shrinkage', and 'shrunk' from our anxiety dictionary, and 'booster', 'expand', 'expands', 'expanding', 'expanded', and 'expansion' from our excitement dictionary.

Third, in our predictive regressions we control for the Jurado, Ludvigson, and Ng (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.

2.3.4 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 the Fama and French (1992) 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:

$$R_{i,t}^e = \alpha_{i,t} + \beta_{i,t}^{MEI*} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \varepsilon_{i,t}, \quad (2)$$

where $R_{i,t}^e$ is the excess return on the stock i in month t . We focus on $\beta_{i,t}^{MEI*}$, stock i 's emotion beta. MEI_t , MKT_t , SMB_t , and HML_t are the monthly market emotion index, market (MKT), small-minus-big (SMB) and high-minus-low (HML) factors at time t , respectively.¹⁶

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

We focus on the magnitude of the conditional emotion beta for several reasons. First, emotional intensity represents 'arousal' in the circumplex model of affect (Posner et al., 2009) and increases with absolute value of valence. Arousal represents the power of the emotions individuals experience that we expect to impact investor decision making in a predictable manner. Second, strength of investor emotion is more salient than its valency. At sufficient

¹⁶ 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.

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.

2.3.5 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.¹⁷ The Fama-French factor data includes the excess market return (MKT), small-minus-big (SMB), high-minus-low (HML), winner-minus-loser (UMD), robust-minus-weak (RMW), and conservative-minus-aggressive (CMA) factors. The liquidity factor (LIQ) is from Lubos Pastor's data library.¹⁸

We compute the book-to-market ratio, denoted BM, as book equity scaled by market equity.¹⁹ 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

¹⁷ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

¹⁸ https://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2018.txt.

¹⁹ 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.

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:

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

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

We also use 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:

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

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

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

As in Hou, Xue, and Zhang (2015), we compute the annual growth rate of total assets, denoted I/A , as the change in book assets scaled by lagged book assets. We also use annual operating profitability, denoted ROE , measured by income before extraordinary items scaled

by one-year-lagged book equity. Finally, we control for the industry effect by assigning each stock to one of the Fama-French ten industry classifications based on Standard Industrial Classification (SIC) codes.

2.4 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.

2.4.1 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 market emotion index (MEI) across time against the S&P 500 to investigate whether the stock market and investor emotions are related. Figure 2.1 shows that the market emotion index captures both the Internet bubble and the Global Financial Crisis periods effectively. We also find expected patterns in the market emotion index following the credit-rating downgrading of the U.S. economy in August 2011 and the collapse in oil prices in early 2016.

The 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 as we have shown is different from investor sentiment. Second, we use both excitement and anxiety words in developing our market emotion index. The correlation between excitement and anxiety words is not large ($\rho = 0.36$) meaning that both excitement and anxiety contain incremental information beyond each other.²⁰ Third, the index is easy to calculate and uses equal weights for word counts as well as for two emotion dimensions i.e., excitement and anxiety. 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 frequencies such as daily and weekly to capture transient changes in investor emotions. Finally, it can also be expanded to other financial markets, asset classes, and is possible to extend far back in time. We also construct several alternative market emotion index measures for robustness purposes.

²⁰ Jiang et al. (2019) find correlations of $\rho = 0.40$ and 0.20 between positive and negative word counts from conference calls, and 10-Ks and 10-Qs respectively in forming their manager sentiment index.

Table 2.1 reports the mean, standard deviation, 25th percentile, median, and 75th percentile of the MEI, emotion beta (β^{MEI}), and characteristics of firms included in our sample. We observe significant cross-sectional variation in firm emotion beta estimates. The variations in firm characteristics such as market capitalization, book-to-market, gross 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.

2.4.2 Fama and MacBeth Regression Estimates

We examine the cross-sectional relation between emotion beta and expected returns using Fama-MacBeth regressions. Table 2.2 presents the time-series averages of the slope coefficients from the regressions of one-month-ahead stock excess returns on emotion beta (β^{MEI}) after controlling for well-known predictors of the cross-section of stock returns. Monthly cross-sectional regressions are estimated using the following specification:

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

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

We also report the correlation between emotion beta and firm characteristics in Table 2.A.2 Panel B. The stock-specific emotion beta has negative correlations with size, book-to-market, and operating profitability ($\rho = -0.26, -0.05$, and -0.15). Emotion beta also shares positive correlations with momentum, reversal, illiquidity, idiosyncratic volatility, growth in assets, and lottery demand ($\rho = 0.19, 0.03, 0.05, 0.29, 0.13$, and 0.25). The low correlations with the firm specific risk factors provide initial evidence that emotion captures incremental information that can have important asset pricing implications.

Panel A of Table 2.2 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.

For example, the average slope when we control for the market factor (see column 2) is 0.83 with a Newey-West t -statistic of 3.48. To determine the economic significance of this

average slope coefficient, we use the average values of the emotion sensitivities in the quintile portfolios. Table 2.3 shows that the difference in emotion beta between high-minus-low quintile portfolios is 0.76 ($= 0.79 - 0.03$) per month. If a stock were to move from the lowest to the highest quintile of β^{MEI} , the change in the stock's average expected return would be a significant increase of 0.68% ($= 0.90 \times 0.76$) per month.

Columns 2 to 6 control for other predictors and still the average slope coefficient of β^{MEI} is positive and significant. In particular, the emotion sensitivity measure β^{MEI} has an estimate of 0.55 with a t -statistic of 4.06 (see column 6). In economic terms, a one-standard-deviation shift in emotion beta is associated with a 1.34% ($= 0.55 \times 2.43$) 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 2.2 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 economically significant up to 8 months in the future. Based on this evidence, we conclude that a stock's emotional utility has a longer-term impact on returns.

2.4.3 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 quintile portfolios and compute equal and value-weighted portfolio returns. Portfolios are rebalanced each month.

Table 2.3 reports emotion beta portfolio characteristics. Average firm size (market capitalization in millions of dollars) monotonically decreases from low emotion beta to high emotion beta quintile 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 higher gross profitability (GP), 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 2.4 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 quintile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}) using different return adjustment models, where quintile 1 (5) contains stocks with the lowest (highest) β^{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 0.54-0.55% per month (t -statistics ranging from 2.42 to 3.80) 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 2.4 reports univariate portfolio results. For each month, we again form quintile portfolios by sorting individual stocks based on their emotion betas (β^{MEI}) for the previous month. The columns of Panel B of Table 2.4 present risk-adjusted abnormal returns (alphas) using two different factor models: (i) α_5 is the intercept from the regression of the excess portfolio returns on a constant, market (MKT), size (SMB), value (HML), operating profitability (RMA), and investment (CMA) factors; and (ii) α_7 is the

alpha relative to the market (MKT), size (SMB), value (HML), momentum (MOM), operating profitability (RMA), investment (CMA), and liquidity (LIQ) factors.

When we consider equal-weighted portfolios, the first column of Table 2.4 Panel B shows that α_5 increases almost monotonically from 0.15% to 0.56% per month. The difference in alpha between the high- β^{MEI} and low- β^{MEI} quintile portfolios is 0.41% per month (or 4.92% per annum) with a Newey-West t -statistic of 5.23. The second column shows the results for the seven-factor model, which are essentially the same. The alphas indicate that after controlling for well-known factors, the return difference between the high- β^{MEI} and low- β^{MEI} stocks remains positive and highly significant.

The last two columns of Table 2.4 Panel B present parallel evidence for β^{MEI} value-weighted portfolios. Consistent with the results for equal-weighted portfolios, value-weighted alpha differences between high- β^{MEI} and low- β^{MEI} portfolios are also positive and significant: $\alpha_5 = 0.49\%$ per month (t -stat. = 2.74); and $\alpha_7 = 0.46\%$ per month (t -stat. = 2.59).

These univariate sorting results support our key conjecture that high emotion beta stocks should earn higher returns than low emotion beta stocks. High-quintile emotion beta stocks are small growth stocks, which are more difficult to value and thus more speculative making them more emotionally charged and thus attractive to investors. This generates price pressure and the economically significant alphas that we report.

2.4.4 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 (2001a); (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 2.5. Columns 1 to 6 control for the Fama-French factors, LIQ, and their interaction with each systematic risk

factor respectively. The last two columns include the interaction of the Fama-French 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 quintiles.

We find that even after controlling for other conditional factors, the value-weighted high-minus-low portfolio alpha is economically significant across all models and weightings. 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 0.41% and 0.45%, respectively, with *t*-statistics of 2.09, and 2.35 (Panel B 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 five- and seven-factor model alpha estimates of 0.49% and 0.46% in Table 2.4 Panel B (columns 3 and 4).

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.

2.4.5 Emotion Beta Persistence and Alpha Longevity

The emotion sensitivities we document in Table 2.4 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 β^{MEI} on the previous 12 months' β^{MEI} s, and lagged cross-sectional predictors. Specifically, each month, we run a regression across firms of 1-year ahead β^{MEI} on lagged β^{MEI} and the following lagged cross-sectional return predictors: market beta (β^{MKT}), market capitalization (Size), volatility beta (β^{VIX}), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth in book assets (I/A), operating profitability (ROE), and lottery demand (MAX).

Column 1 of the first row of Table 2.6 presents the univariate regressions of β^{MEI} on previous 12 months' β^{MEI} . The coefficient is large and statistically significant, which implies that stocks with high β^{MEI} exhibit a similar pattern in the following 12 months. We repeat the same process for up to 5 years ahead, and continue to find statistically significant results. The second row of Table 2.6 shows that after adding cross-sectional return predictors, coefficients

remain large and significant. β^{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 2.2 shows the effect of varying the portfolio formation lag from 1 to 12 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 four months.

We vary the holding period of the high-minus-low emotion beta-based portfolio in Panel B of Figure 2.2. 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 of more than 3-months, a high-minus-low trading strategy does not generate any alpha. Not surprisingly, this evidence suggests that stock emotional charge decays over time.

2.4.6 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 (β^{MEI}), we estimate mood (β^{Mood}), sentiment (β^{SENT}), uncertainty (β^{UNC}), and tone (β^{LM} , and β^{HN}) betas by running rolling regressions similar to equation (2). We first examine their correlations, and then include them in Fama-MacBeth regressions.

The correlation matrix in Appendix Table 2.A.2 Panel A, shows that emotion beta is not highly correlated with mood, sentiment, uncertainty, or tone betas. In fact, the highest correlation is only 0.268 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.

2.4.6.1 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 ($XRET_{A,MoodMonth}$):

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

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

Table 2.7, 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, β^{MEI} has a significant coefficient with a t -statistic of 2.29. In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 1.12% ($= 0.46 \times 2.43$) 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.

It is possible that emotion beta will have low or no predictability during high and low mood periods because during these high (low) mood positively (negatively) predicts stock returns (see Hirshleifer et al., 2020). To examine this possibility, we rerun the Fama-Macbeth regressions during high (low) mood periods separately with results presented in Appendix Table 2.A.3. Mood betas, as expected, have positive (negative) predictability. However, our emotion betas during these periods are still highly significant (t -statistics of 6.09 and 2.94, respectively). This evidence indicates that emotion beta has incremental predictive power over mood in explaining the variation in the cross-section of future stock returns in both high and low mood market states.

2.4.6.2 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)²¹ investor sentiment index orthogonalized for macro-variables, and the University of Michigan's Consumer Confidence Index (UMCCI)²², after controlling for the Fama-French three factors separately:²³

$$R_{i,t}^e = \alpha_i + \beta_{i,t}^{SENT} SENT_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \varepsilon_{i,t}, \quad (8)$$

$$R_{i,t}^e = \alpha_i + \beta_{i,t}^{UMCCI} UMCCI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \varepsilon_{i,t}, \quad (9)$$

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

Table 2.7 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 0.46, and 0.49 and *t*-statistics of 3.65, and 3.91, respectively. Thus, emotion beta is different from sentiment betas and has incremental ability to explain the cross-sectional variation in returns.

2.4.6.3 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.

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 ($R_{I/A}$), and profitability (ROE) factors:

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

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

²³ 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.

$$R_{i,t}^e = \alpha_i + \beta_{i,t}^{UNC} UNC_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{MOM} MOM_t + \beta_{i,t}^{LIQ} LIQ_t + \beta_{i,t}^{R_{I/A}} R_{I/A,t} + \beta_{i,t}^{ROE} ROE_t + \varepsilon_{i,t}. \quad (10)$$

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 (β^{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 Fama-French three factors:

$$R_{i,t}^e = \alpha_i + \beta_{i,t}^{EPU} EPU_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \varepsilon_{i,t}, \quad (11)$$

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 2.7 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 0.43 and 0.42 and t -statistics of 3.36 and 3.38 respectively. Thus, we conclude that emotion betas do not capture the effects of economic uncertainty.

2.4.6.4 Is Emotion Beta Capturing Tone?

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

First, we explore for potential commonality across LM's positive/negative and our emotion-based word lists. Table 2.A.4 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 2.A.5. If both MEI and tone are measuring the same thing, then the diagonal elements should account

²⁴ 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 .

for most of the news articles. However, the diagonal elements only account for 26.5% 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 A Case Study 2.A.1 and 2.A.2). The first article (*The New York Times*, February 28, 2012) elicits net excitement with the market emotion index score = 0.50. 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 with this feeding into their economic decisions.

The second article (*The Wall Street Journal*, October 6, 2007) has a market emotion index = -0.40 reflecting net anxiety. Again, the reasons for the negative index are clear, as conveyed in the conclusion at the end that “... *holding (stocks) requires a stronger stomach today than a year ago*”. Nonetheless, actual tone remains neutral (= 0.02). 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 Fama-French three factors:

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

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

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 2.7, columns 6 and 7 report the results of the two cross-sectional regressions. Again, even after accounting for the LM and HN tone measures β^{MEI} still has highly significant coefficients (t -statistics = 3.72 and 3.75 respectively). In economic terms, a one-standard-deviation shift in emotion sensitivity is associated with a 1.12% ($= 0.46 \times 2.43$) 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 2.7, 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.

2.4.7 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 quintiles based on SIZE and then, within each SIZE quintile, we sort stocks into further quintiles based on B/M so that quintile 1 (quintile 5) contains stocks with the lowest (highest) market capitalization and book-to-market values.

Table 2.8, Panel A presents the average emotion beta across the bivariate quintiles. 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 β^{MEI} for quintile (1,1) is fivefold that for quintile (5,5) 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 four firm characteristics: market capitalization (SIZE), book-to-market (B/M), gross profitability (GP), and annual growth of book assets (I/A). Table 2.8 also reports the results of the conditional bivariate sorts between individual firm characteristics and emotion beta. We report both equal-weighted (Panel B), and value-weighted (Panel C) 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 quintile portfolios based on SIZE. Then, within each SIZE quintile, we further sort stocks based on emotion beta (β^{MEI}) into quintile portfolios. We average portfolio returns across the five SIZE quintiles to produce quintile portfolios with dispersion in β^{MEI} , but that contain stocks across all market

capitalizations (see Bali et al., 2017). This process creates a set of β^{MEI} portfolios with very similar levels of market capitalization, and hence controls for differences in SIZE.

The first column in Panel B of Table 2.8 shows that after controlling for SIZE, the equal-weighted difference in the abnormal return spread between high and low emotion beta small stocks is 0.43% per month with a t -statistic of 4.82. We find similar results using value-weighted portfolio returns (column 1 in Panel C). 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, and annual growth in assets 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 with both equal- and value-weighted portfolio returns. Our results indicate that well-known cross-sectional return predictors cannot explain the emotion beta premium.

2.4.8 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 factors can explain the returns generated by an emotion beta-based factor.

We form our emotion beta factor (EBF) 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 β^{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., $EBF = (r_{SH} + r_{BH})/2 - (r_{SL} + r_{BL})/2$.

Table 2.9 shows that the value-weighted emotion beta factor generates an average monthly return of 0.44% with a Newey-West t -statistic of 2.62. We also estimate the emotion beta factor alpha using other factor models. We find that the alphas remain positive, ranging from 0.30% to 0.66%, and significant with t -statistics ranging from 2.94 to 4.13. We find qualitatively similar results when the emotion beta factor is constructed with equal-weighted

returns. As shown in the second row of Table 2.9, the equal-weighted emotion beta factor generates an average monthly return of 0.81% with a t -statistic of 4.92, with the associated alphas also economically meaningful, and statistically significant. These results indicate that well-known risk factors cannot explain the variation in 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 2.2 shows that our emotion beta factor in the Fama-MacBeth cross-sectional regressions meets this hurdle in virtually all cases with t -statistics ranging between 3.12 and 4.06, and only dropping below this level controlling for momentum with a t -statistic of 2.80. In parallel, we find in Table 2.9 that the equal-weighted (value-weighted) emotion beta passes this test with t -statistic of 4.92 (2.62). With virtually all t -statistics greater than 3.00 in our Fama-MacBeth analyses, we also provide evidence that emotion beta is different from mood, sentiment, uncertainty, and narrative tone.

2.5 Additional Results

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

2.5.1 Alternative Measures of Emotion Beta

To begin, we test whether alternative measures of emotion sensitivity (β^{MEI}) predict future stock returns. In our baseline analysis, we control for the Fama-French three 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 β^{MEI} . First, we control only for the market (MKT) factor, then the market (MKT), size (SMB), value (HML), and momentum (MOM) factors, and finally, following Bali et al. (2017), the market (MKT), size (SMB), value (HML), momentum (MOM), investment (IVA), profitability (ROE), and liquidity (LIQ) factors:

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

$$\begin{aligned} \text{Model 2: } R_{i,t}^e = & \alpha_{i,t} + \beta_{i,t}^{MEI^b} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t \\ & + \beta_{i,t}^{MOM} MOM_t + \varepsilon_{i,t}, \end{aligned} \quad (15)$$

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

$$+\beta_{i,t}^{MOM}MOM_t + \beta_{i,t}^{R1/A}R_{1/A,t} + \beta_{i,t}^{ROE}ROE_t + \beta_{i,t}^{LIQ}LIQ_t + \varepsilon_{i,t}, \quad (16)$$

After generating β^{MEI^a} , β^{MEI^b} , and β^{MEI^c} from these three specifications, we form equal-weighted and value-weighted portfolios and compute factor alphas for each emotion beta quintile. Panels A, B, and C of Table 2.10 shows that for all these models, β^{MEI} produces a positive and significant alpha for both equal and value-weighted portfolios. The results presented in Table 2.10, along with those reported in Table 2.4, indicate that even using alternative specifications to measure firm-level emotional utility, emotion beta remains a significant predictor of future stock returns.

2.5.2 Subsample Estimates

Next, we examine whether microcap stocks are driving our results, in the light of previous evidence that small stocks often drive mispricing (see, for example, Baker and Wurgler, 2006). Also, we investigate whether the trading strategy of going long in high emotion beta stocks and shorting low emotion beta stocks is robust across S&P 500, largest 1000, and the most liquid 1000 stocks.

To control for microcaps as small firms exhibit high emotion beta, we follow the definition of Ball et al. (2020) and only include stocks with market values of equity at or above the 20th percentile of market capitalization. Panel A of Table 2.11 presents the alphas of univariate emotion beta portfolios excluding microcap stocks from the sample. Column 1 of Panel A shows a high-minus-low investment strategy produces positive and significant alphas of 0.38% per month (t -statistic = 2.39).²⁵ This evidence suggests that the mispricing identified by the emotion beta is not driven by microcap stocks.

We also investigate if the emotion beta premium is driven by smaller, illiquid, or low-priced stocks. Specifically, we test whether emotion beta still generates a premium for S&P 500, largest 1,000 stocks based on market capitalization, and 1,000 most liquid stocks based on Amihud's (2002) illiquidity measure. Columns 2 to 4 of Table 2.11 present the respective seven-factor alpha (α_7) spreads between high- β^{MEI} and low- β^{MEI} portfolio returns. In the case of S&P 500 stocks, this spread is 0.45% per month (t -statistic = 2.58), 0.42% per month (t -statistic = 2.70) for the largest 1,000 stocks, and 0.39% per month (t -statistic = 2.41) for the

²⁵ When we employ equal-weighting, the high-minus-low emotion sensitive trading strategy yields an alpha of 0.49% with Newey-West t -statistic of 5.36.

1,000 most liquid stocks. Thus, our evidence of emotion premium is not exclusive to small, illiquid and low-priced stocks.

2.5.3 Alternative Market Emotion Indexes

In the next set of tests, we construct the market emotion index in different ways. We use several variations of the market emotion index to estimate emotion beta and test the performance of high-minus-low emotion beta-based trading strategies.

First, we construct a standardized market emotion index with a mean of zero and standard deviation of one. Second, we time weight the market emotion index where MEI for day d receives more weight than MEI for day $d-1$, computing monthly MEI by weighting daily MEIs by their respective time-weights (Time-weighted $MEI_t = \sum_{d=1}^t MEI_d \times weight_d$). Third, we generate ‘Total MEI’ calculated as the ratio of the sum of excitement and anxiety words to total words in a month ($Total\ MEI_t = \frac{Excitement_t + Anxiety_t}{Total\ Words_t}$). Fourth, we derive ‘Net MEI’ calculated as the ratio of the difference between excitement and anxiety words to total words in a month ($Net\ MEI_t = \frac{Excitement_t - Anxiety_t}{Total\ Words_t}$).

Panel B of Table 2.11 presents the results from using different variations of the market emotion index. A high-minus-low emotion beta investment strategy generates a positive and significant alpha irrespective of the construction of the MEI measure (see columns 1 to 4 of Panel B). These results show that emotion beta-based mispricing is robust, and does not depend on how the market emotion index is measured.

2.5.4 Valency-based Emotion Premium

In all our analyses so far, we work with the absolute beta derived using equation (2) under the assumption that investors be driven by the strength of emotional arousal or charge stocks have for them rather than by valency, i.e., their notional goodness or badness (or, positivity or negativity). Specifically, trend chasers and contrarians are likely to be more active during bullish and bearish periods creating temporary price pressure. To provide evidence in favor of using absolute emotion beta, we split our full sample based on asymmetric emotion beta and test whether a high-minus-low emotion beta-based trading strategy still earns economically significant alpha.²⁶

²⁶ It is interesting to note the very strong results for Total MEI with high-minus-low alpha of 0.86% per month and Newey-West t -statistic of 4.11. This would be consistent with the main component of the market emotion

Specifically, we first take stocks with β^{MEI} above the asymmetric beta median, which mainly have large positive values. Next, we sort these stocks in ascending order into quintiles where the high (low) portfolio contains the most (least) positive emotion beta stocks. Table 2.11, Panel C column 1, provides the results of univariate sorts based on above median emotion betas. We find that a high-minus-low trading strategy generates economically significant alpha after controlling for well-known asset-pricing factors.

We then take stocks with β^{MEI} s below the median of the asymmetric beta, which typically have large negative values, and sort these stocks in descending order into quintiles where the high (low) portfolio contains most (least) negative emotion beta stocks in a similar way. Panel C column 2 provides parallel results for the univariate sorts based on below median emotion betas. Again, the high-minus-low trading strategy generates an economically significant alpha.

Next, we examine whether the excitement and anxiety emotions we use to derive the market emotion index capture different sources of mispricing reflecting emotional valency. We estimate the excitement beta using equation (2) where we use ‘Excitement’ as the proportion of excitement words scaled by total words in a month. We do the same in estimating the anxiety beta. Columns 3 and 4 in Panel C report the results for excitement and anxiety betas respectively. Irrespective of the valence of the emotion, we find qualitatively similar results to those reported in Table 2.4. This finding suggests that it is not emotional valency that is driving our results but the strength of the emotional charge or arousal, again, supportive empirically of the affective circumplex model of emotions of Posner et al. (2009).

Taken together, the results from Panel C of Table 2.11 provide evidence consistent with our assertion that investors act based on the absolute value of the emotional charge rather than on emotional valency. The stronger the emotion, the greater the quintile alpha, independent of whether it is the excitement or anxiety β^{MEI} which is being used. Thus, the absolute emotion beta measure correctly identifies investors' emotional sensitivity to stocks leading to the related mispricing we find in the broad cross-section of the U.S. stock market.

index being arousal, i.e., strength of emotional charge, consistent with the affective circumplex model. Both excitement and anxiety generate emotional charge in the same direction.

2.5.5 Extreme Portfolio Alpha

All our portfolio level analysis so far has been based on quintile 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 2.3 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 2.3 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, different stock subsamples, different ways of measuring our market emotion index, or construct different numbers of stock portfolios, results are very similar. All these robustness tests concur with our main findings that stock emotional utility is an important predictor of the cross-section of stock returns.

2.6 Summary and Conclusions

Casual observation of investors in financial markets indicate that investor emotions are influential in driving their investment decisions. Emotional engagement of investors with certain subset of stocks could influence their decision making and systematically affect the composition of their portfolios. The strength of this relation would, in turn, influence asset prices in market segments that are emotion-sensitive. In this study, we focus on integral emotions of anxiety and excitement, 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 annualized alpha of 4.92% during the 1995-2018 period. This evidence of predictability is robust and extends up to 4-8 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 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.

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 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.

Figure 2. 1: Emotion and S&P 500 Index Overtime

The figure shows the relationship between market emotion index (MEI) and S&P 500 index over time. Market emotion index is measured as the ratio of difference between excitement and anxiety to the total of excitement and anxiety word counts. We use news articles over a month to get the monthly word counts for excitement and anxiety. The shaded areas represent NBER recession periods. The sample period is from January 1990 to December 2018.

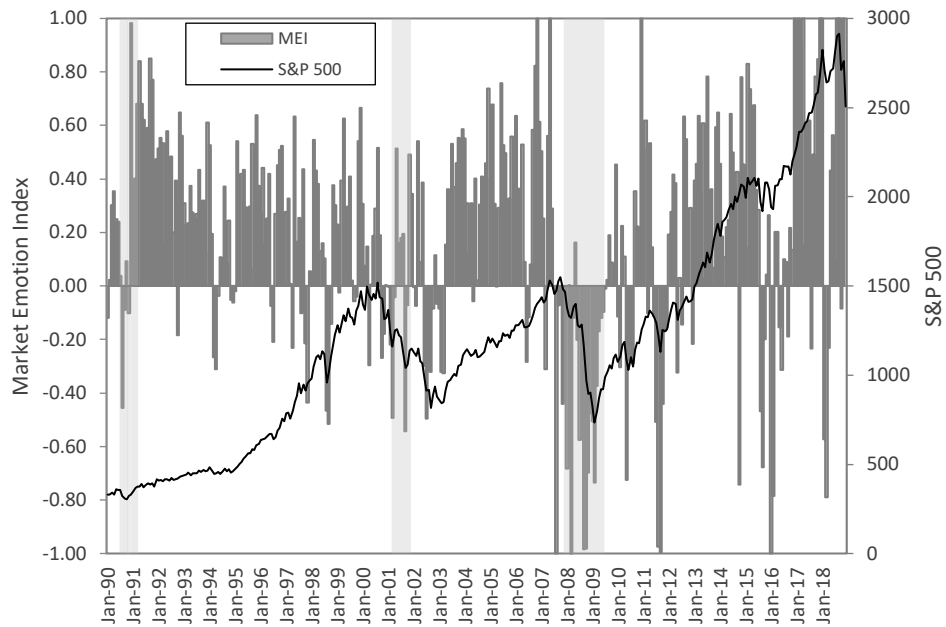


Figure 2. 2: Longevity of Alpha

The figure presents a series of Long-Short trading strategy alphas for different portfolios formed on emotion beta (β^{MEI}). For each month, we form portfolios based on emotion sensitivities, where Short (Long) portfolio contains stocks with the lowest (highest) β^{MEI} during the previous formation months. In Panel A, we examine the longevity of high-minus-low emotion beta-based trading strategy alphas. We keep on increasing the gap from 1 to 12 months 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 3 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 dotted red line represents t -statistics at 90% confidence level. The estimation period is from January 1995 to December 2018.

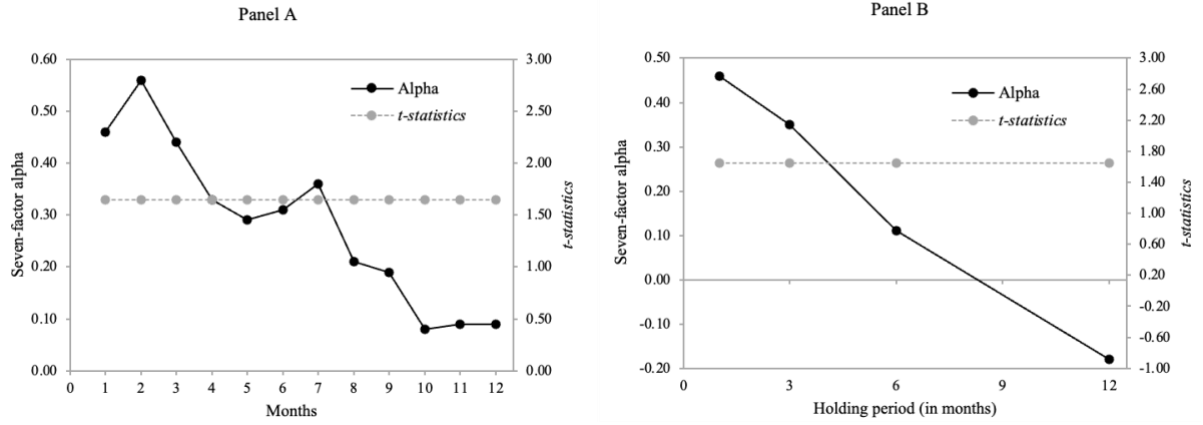


Figure 2. 3: Extreme Portfolio Alpha

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) β^{MEI} during the previous formation months. The seven-factor alphas are relative to market (MKT), size (SMB), value (HML), momentum (MOM), investment (CMA), profitability (RMW), and liquidity (LIQ) factors. The dotted red line represents t -statistic at 95% confidence level. The estimation period is from January 1995 to December 2018.

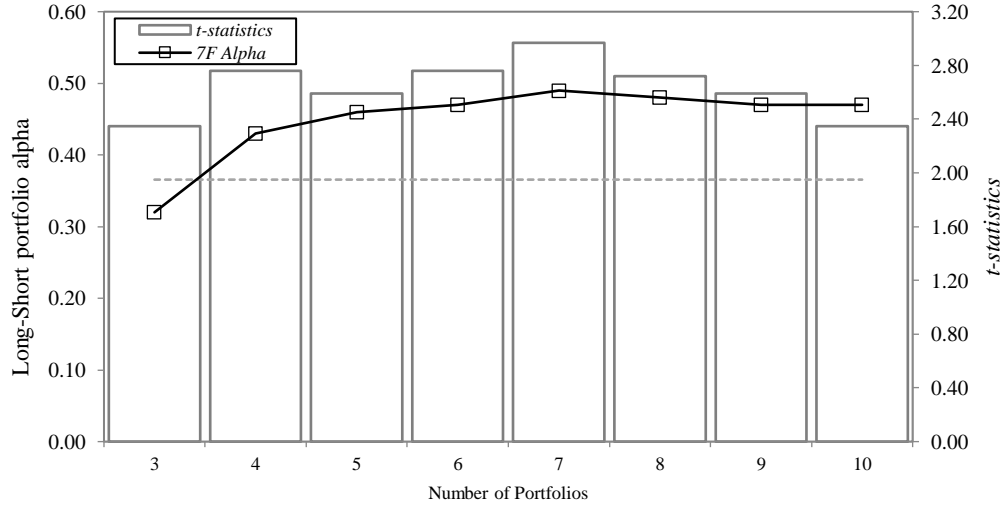


Table 2. 1: Summary Statistics

This table reports the mean, standard deviation, 25th percentile, median, and 75th percentile of the market emotion index (MEI), emotion beta (β^{MEI}), and other firm characteristics. Market emotion index is measured as the ratio of difference between excitement and anxiety to the total of excitement and anxiety word counts. We use news articles over a month to get the monthly word counts for excitement and anxiety. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and Fama-French three-factors—market, size, and value. Then we take absolute value of emotion beta. Firm characteristics are SIZE (market capitalization in millions of dollars), book-to-market ratio (B/M), gross profitability (GP), 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 1995 to December 2018.

| | Mean | Standard deviation | 25 th percentile | Median | 75 th percentile |
|------------------|----------|--------------------|-----------------------------|---------|-----------------------------|
| MEI | 0.178 | 0.082 | 0.134 | 0.188 | 0.239 |
| β^{MEI*} | 0.004 | 2.448 | -0.152 | -0.004 | 0.151 |
| $ \beta^{MEI*} $ | 0.291 | 2.431 | 0.067 | 0.152 | 0.298 |
| SIZE | 5748.390 | 23892.870 | 215.523 | 775.576 | 2877.280 |
| B/M | 0.652 | 0.751 | 0.316 | 0.520 | 0.808 |
| GP | 0.361 | 0.262 | 0.195 | 0.323 | 0.483 |
| MOM | 0.208 | 0.673 | -0.101 | 0.109 | 0.357 |
| REV | 0.011 | 0.141 | -0.053 | 0.007 | 0.069 |
| ILLIQ | 0.052 | 1.180 | 0.000 | 0.000 | 0.003 |
| IVOL | 0.020 | 0.014 | 0.011 | 0.017 | 0.025 |
| I/A | 0.152 | 0.577 | -0.007 | 0.065 | 0.174 |
| ROE | 0.070 | 0.946 | 0.035 | 0.095 | 0.159 |
| MAX | 0.032 | 0.021 | 0.018 | 0.027 | 0.039 |

Table 2. 2: Fama-MacBeth Cross-sectional Regression Estimates

The table reports the time-series averages of the slope coefficients obtained from regressing monthly excess stock returns (in percentage) on previous months emotion beta (β^{MEI}) and a set of lagged control variables using the Fama-MacBeth method. The control variables are market beta (β^{MKT}), volatility beta (β^{VIX}), log market capitalization (Size), book-to-market ratio (B/M), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), idiosyncratic volatility (IVOL), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). Panel B presents the results from regressing monthly excess returns in two- to 12-months ahead against β^{MEI} after controlling for all other predictive variables and for brevity, we do not report their intercepts, and coefficients. The t -statistics are computed after adjusting for Newey-West (1987) standard errors and are reported 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) |
| β^{MEI} | 0.90 (3.49) | 0.83 (3.48) | 0.80 (3.37) | 0.52 (3.09) | 0.47 (3.46) | 0.55 (4.06) | 0.77 (3.85) | 0.73 (3.94) | 0.70 (3.71) | 0.41 (2.80) | 0.39 (3.12) | 0.45 (3.65) |
| β^{MKT} | | 0.10 (0.91) | 0.09 (0.89) | 0.13 (1.26) | 0.08 (0.95) | 0.13 (1.48) | | 0.09 (1.00) | 0.08 (0.87) | 0.12 (1.44) | 0.10 (1.30) | 0.14 (1.79) |
| β^{VIX} | | | -0.12 (-0.41) | -0.32 (-1.23) | -0.50 (-2.15) | -0.31 (-1.40) | | | -0.08 (-0.33) | -0.27 (-1.22) | -0.44 (-2.23) | -0.28 (-1.51) |
| Size | | | | -0.16 (-4.23) | -0.18 (-4.96) | -0.16 (-4.68) | | | | -0.15 (-4.28) | -0.17 (-5.19) | -0.16 (-4.90) |
| B/M | | | | 0.14 (1.73) | 0.23 (3.16) | 0.23 (3.27) | | | | 0.21 (3.24) | 0.28 (4.62) | 0.29 (4.77) |
| MOM | | | | 0.07 (0.34) | -0.10 (-0.55) | -0.11 (-0.58) | | | | 0.05 (0.27) | -0.12 (-0.71) | -0.13 (-0.71) |
| REV | | | | | -1.02 (-1.95) | -1.18 (-2.24) | | | | | -1.17 (-2.46) | -1.34 (-2.76) |
| ILLIQ | | | | | -0.81 (-1.92) | -0.90 (-2.12) | | | | | -0.74 (-1.81) | -0.83 (-2.01) |
| IVOL | | | | | 0.07 (1.29) | 0.41 (5.94) | | | | | 0.05 (1.15) | 0.41 (6.55) |
| I/A | | | | | 0.43 (3.38) | 0.46 (3.66) | | | | | 0.37 (3.14) | 0.40 (3.46) |
| ROE | | | | | 1.46 (5.73) | 1.43 (5.85) | | | | | 1.55 (6.64) | 1.52 (6.67) |
| MAX | | | | | | -0.28 (-4.74) | | | | | | -0.29 (-5.68) |
| Intercept | 0.89 (3.25) | 0.81 (3.54) | 0.85 (3.59) | 1.94 (5.22) | 1.84 (5.08) | 1.89 (5.30) | 0.72 (2.08) | 0.66 (2.16) | 0.81 (2.67) | 2.07 (5.17) | 0.76 (2.59) | 1.05 (4.23) |
| Adj. R-squared | 0.56% | 1.43% | 1.75% | 3.78% | 5.76% | 6.18% | 4.50% | 5.07% | 5.38% | 6.93% | 8.56% | 8.89% |
| N months | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 287 |

Table 2. 2: Continued

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

Table 2. 3: Characteristics of Emotion Beta Sorted Portfolios

The table reports the characteristics of portfolios sorted on emotion beta. For each month, we form quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. Columns 1 to 6 present the average emotion beta (β^{MEI}), market beta (β^{MKT}), size (market capitalization in millions of dollars), book-to-market ratio (B/M), gross profitability (GP), annual growth of assets (I/A), idiosyncratic volatility (IVOL), illiquidity (ILLIQ), and demand for lottery-like stocks (MAX) across portfolios. The estimation period is from January 1995 to December 2018.

| | Portfolios | | | | | |
|---------------|------------|----------|----------|----------|----------|-----------------------|
| | Low | 2 | 3 | 4 | High | High-Low |
| β^{MEI} | 0.03 | 0.09 | 0.16 | 0.27 | 0.79 | 0.76 (15.83) |
| β^{MKT} | 0.94 | 0.96 | 1.00 | 1.07 | 1.21 | 0.27 (6.55) |
| Size | 6,646.54 | 6,341.04 | 5,535.86 | 3,940.66 | 1,885.06 | -4,761.48 (-16.46) |
| B/M | 1.24 | 1.24 | 1.23 | 1.18 | 1.01 | -0.23 (-6.30) |
| GP | 0.35 | 0.35 | 0.36 | 0.37 | 0.37 | 0.02 (4.36) |
| I/A | 0.11 | 0.12 | 0.12 | 0.13 | 0.18 | 0.07 (14.15) |
| IVOL | 0.17 | 0.18 | 0.19 | 0.20 | 0.25 | 0.08 (26.60) |
| ILLIQ | 0.04 | 0.04 | 0.05 | 0.05 | 0.07 | 0.03 (2.67) |
| MAX | 0.28 | 0.29 | 0.30 | 0.32 | 0.39 | 0.11 (21.06) |

Table 2. 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 quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. In Panel A, column 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. The last row presents the differences between high and low β^{MEI} portfolio returns. Panel B presents emotion beta-based portfolio alphas. Columns 1 and 2 report the alphas (α_5 and α_7) for equal-weighted portfolios. Columns 3 and 4 report the same for value-weighted portfolios. α_5 is the alpha relative to market, size, value, profitability, and investment factors; α_7 is the alpha relative to market, size, value, momentum, profitability, investment, and liquidity factors. The last row presents alphas for high-minus-low portfolios. The t -statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| Panel A: Portfolio average excess returns across return adjustment models | | | | |
|---|----------------|----------------|------------------------|--------------------------|
| Portfolios | RET-RF | DGTW return | Market-adjusted return | Industry-adjusted return |
| Low | 1.06 | 0.27 | 0.44 | 0.26 |
| 2 | 0.96 | 0.22 | 0.34 | 0.21 |
| 3 | 0.98 | 0.23 | 0.36 | 0.22 |
| 4 | 1.15 | 0.31 | 0.53 | 0.43 |
| High | 1.60 | 0.81 | 0.98 | 0.81 |
| High-Low | 0.54 (2.43) | 0.54 (3.80) | 0.54 (2.42) | 0.55 (3.19) |
| Panel B: Portfolio alphas using unconditional factor models | | | | |
| Portfolios | Equal-weighted | | Value-weighted | |
| | α_5 | α_7 | α_5 | α_7 |
| Low | 0.15 | 0.17 | 0.42 | 0.44 |
| 2 | 0.08 | 0.10 | 0.24 | 0.24 |
| 3 | 0.13 | 0.17 | 0.31 | 0.33 |
| 4 | 0.22 | 0.26 | 0.38 | 0.35 |
| High | 0.56 | 0.59 | 0.91 | 0.90 |
| High-Low | 0.41 (5.23) | 0.42 (5.15) | 0.49 (2.74) | 0.46 (2.59) |

Table 2. 5: Emotion Beta Sorted Portfolios: Conditional Factor Model Estimates

The table presents portfolio alphas based on conditional factor models. For each month, we form quintile portfolios by sorting stocks based on their emotion beta (β^{MEI}), where quintile 1 (5) contains stocks with the lowest (highest) β^{MEI} during the previous month. Panel A and Panel B present both equal- and value-weighted portfolio alphas, respectively, 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 (2001a); (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 in each panel include interaction with all the time-varying U.S. systematic risk factors with Fama-French and LIQ factors at the same time. The last two rows in each panel present the differences between high and low portfolio alphas. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| Panel A: Equal-weighted | | | | | | | | |
|-------------------------|------------------------|---------------------------|------------------------|-------------------------|-------------------------|-------------------------|----------------|------------------------------------|
| Portfolios | $\alpha_{FF6+LIQ+REC}$ | $\alpha_{FF6+LIQ+EXTMKT}$ | $\alpha_{FF6+LIQ+cay}$ | $\alpha_{FF6+LIQ+pspd}$ | $\alpha_{FF6+LIQ+tspd}$ | $\alpha_{FF6+LIQ+dspd}$ | α_{all} | $\alpha_{all \text{ with EXTMKT}}$ |
| Low | 0.16 | 0.10 | 0.11 | 0.13 | 0.12 | 0.12 | 0.12 | 0.11 |
| 2 | 0.07 | 0.03 | 0.03 | 0.07 | 0.05 | 0.07 | 0.04 | 0.04 |
| 3 | 0.13 | 0.07 | 0.09 | 0.13 | 0.12 | 0.12 | 0.11 | 0.09 |
| 4 | 0.24 | 0.19 | 0.17 | 0.22 | 0.21 | 0.21 | 0.23 | 0.21 |
| High | 0.42 | 0.42 | 0.38 | 0.43 | 0.42 | 0.41 | 0.36 | 0.37 |
| High-Low | 0.26 (2.88) | 0.32 (3.87) | 0.27 (3.25) | 0.30 (3.82) | 0.30 (3.78) | 0.29 (3.29) | 0.24 (2.84) | 0.26 (3.10) |
| Panel B: Value-weighted | | | | | | | | |
| Portfolios | $\alpha_{FF6+LIQ+REC}$ | $\alpha_{FF6+LIQ+EXTMKT}$ | $\alpha_{FF6+LIQ+cay}$ | $\alpha_{FF6+LIQ+pspd}$ | $\alpha_{FF6+LIQ+tspd}$ | $\alpha_{FF6+LIQ+dspd}$ | α_{all} | $\alpha_{all \text{ with EXTMKT}}$ |
| Low | 0.46 | 0.44 | 0.45 | 0.44 | 0.44 | 0.46 | 0.40 | 0.42 |
| 2 | 0.26 | 0.25 | 0.26 | 0.26 | 0.25 | 0.27 | 0.21 | 0.23 |
| 3 | 0.34 | 0.34 | 0.35 | 0.37 | 0.38 | 0.34 | 0.37 | 0.35 |
| 4 | 0.29 | 0.35 | 0.30 | 0.30 | 0.32 | 0.31 | 0.36 | 0.32 |
| High | 0.87 | 0.99 | 0.90 | 0.92 | 0.90 | 0.92 | 0.98 | 0.92 |
| High-Low | 0.41 (2.09) | 0.55 (3.16) | 0.45 (2.35) | 0.48 (2.68) | 0.46 (2.65) | 0.46 (2.40) | 0.58 (2.93) | 0.50 (2.65) |

Table 2. 6: Persistence in Emotion Beta

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

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

Table 2. 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 2.2) using Fama-MacBeth methodology. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and Fama-French three-factors—market, size, and value. Then, we take the absolute value of β^{MEI} . The mood beta (β^{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 (β^{SENT}) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. We generate the consumer confidence beta (β^{UMCCI}) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and Fama-French three-factors. Following Bali et al. (2017), we compute the uncertainty beta (β^{UNC}) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta (β^{EPU}) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and Fama-French three-factors. We derive two tone betas (β^{LM} and β^{HN}) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and Fama-French three-factors. 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. 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) |
|------------------------------|------------------|----------------|------------------|------------------|------------------|----------------|----------------|------------------|------------------|
| β^{MEI} | 0.46 (2.29) | 0.46 (3.65) | 0.49 (3.91) | 0.43 (3.36) | 0.42 (3.38) | 0.46 (3.72) | 0.45 (3.75) | 0.44 (3.55) | 0.35 (1.97) |
| β^{Mood} | -0.10 (-0.36) | | | | | | | | -0.13 (-0.47) |
| β^{SENT} | | 0.79 (0.98) | | | | | | 0.47 (0.56) | 1.17 (0.79) |
| β^{UMCCI} | | | -3.49 (-0.26) | | | | | -1.53 (-0.72) | -2.33 (-0.62) |
| β^{UNC} | | | | -0.08 (-1.23) | | | | -0.15 (-2.06) | -0.25 (-1.89) |
| β^{EPU} | | | | | -0.15 (-0.33) | | | 0.49 (1.19) | 0.27 (0.37) |
| β^{LM} | | | | | | 0.21 (1.19) | | 0.35 (1.48) | 0.47 (1.02) |
| β^{HN} | | | | | | | 0.15 (0.58) | 0.20 (0.60) | 0.09 (0.20) |
| Firm controls & risk factors | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. R-Squared | 10.68% | 9.10% | 9.10% | 9.10% | 9.05% | 9.07% | 9.09% | 9.07% | 11.63% |
| N months | 137 | 287 | 287 | 287 | 287 | 287 | 287 | 287 | 137 |

Table 2. 8: Emotion Beta Estimates for Bivariate Sorted Portfolios

The table shows results from bivariate sorts. Panel A reports average emotion beta (β^{MEI}) across size and book-to-market quintiles. First, stocks are sorted based on SIZE (market capitalization) into quintile portfolios and then, each of the SIZE quintiles are sorted again on book-to-market. After bivariate sorting, the table reports average emotion beta across quintiles. In Panel B and C, stocks are first sorted into quintiles based on a firm characteristic, and then within each characteristic quintile stocks are further sorted into quintiles based on emotion beta (β^{MEI}). For each emotion beta quintile, we average alphas across the five characteristic groups. The firm characteristics are market capitalization (SIZE), book-to-market (B/M), gross profitability (GP), and annual growth of book assets (I/A). We report both equal- and value-weighted seven-factor alphas (in percentage) relative to the market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), investment (CMA), and liquidity (LIQ) factors. 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 | Big |
| Book-to-Market | Low | 0.67 | 0.46 | 0.49 | 0.24 | 0.15 |
| | 2 | 0.38 | 0.30 | 0.24 | 0.19 | 0.14 |
| | 3 | 0.29 | 0.25 | 0.22 | 0.17 | 0.14 |
| | 4 | 0.26 | 0.23 | 0.20 | 0.17 | 0.14 |
| | High | 0.25 | 0.21 | 0.18 | 0.16 | 0.13 |
| Panel B: Equal-weighted | | | | | | |
| Portfolios | SIZE | B/M | GP | I/A | | |
| Low | 0.09 | 0.09 | 0.10 | 0.10 | | |
| 2 | 0.06 | 0.07 | 0.08 | 0.10 | | |
| 3 | 0.08 | 0.02 | 0.04 | 0.04 | | |
| 4 | 0.15 | 0.14 | 0.11 | 0.12 | | |
| High | 0.52 | 0.31 | 0.30 | 0.31 | | |
| High-Low | 0.43 | 0.22 | 0.20 | 0.21 | | |
| | (4.82) | (2.40) | (2.27) | (2.50) | | |
| Panel C: Value-weighted | | | | | | |
| Portfolios | SIZE | B/M | GP | I/A | | |
| Low | 0.31 | 0.38 | 0.44 | 0.35 | | |
| 2 | 0.38 | 0.25 | 0.27 | 0.36 | | |
| 3 | 0.28 | 0.28 | 0.23 | 0.23 | | |
| 4 | 0.29 | 0.27 | 0.30 | 0.32 | | |
| High | 0.66 | 0.91 | 0.89 | 0.73 | | |
| High-Low | 0.35 | 0.53 | 0.45 | 0.38 | | |
| | (2.16) | (2.61) | (2.39) | (2.12) | | |

Table 2. 9: Performance Estimates: Emotion Beta-based Factor

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

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

Table 2. 10: Alpha Estimates for Emotion Beta Sorted Portfolios: Alternative Models

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

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

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

$$\text{Model 3: } R_{t+1}^e = \alpha_{i,t} + \beta_{i,t}^{MEI^c} MEI_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{MOM} MOM_t \\ + \beta_{i,t}^{R_{I/A}} R_{I/A,t} + \beta_{i,t}^{ROE} ROE_t + \beta_{i,t}^{LIQ} LIQ_t + \varepsilon_{i,t},$$

Model 1 controls for the market (MKT) factor. Model 2 controls for the market (MKT), size (SMB), value (HML), and momentum (MOM) factors. Finally, Model 3, controls for the market (MKT), size (SMB), value (HML), momentum (MOM), investment ($R_{I/A}$), profitability (ROE), and liquidity (LIQ) factors. The columns 1 and 2 report the alphas (α_5 and α_7) for equal-weighted portfolios. The columns 3 and 4 report the same for value-weighted portfolios. α_5 is the alpha relative to market, size, value, profitability, and investment factors; and α_7 is the alpha relative to the market, size, value, momentum, profitability, investment, and liquidity factors. The last row in each panel presents the alpha differences between high and low portfolios. The t -statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

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

| Portfolios | Equal-weighted | | Value-weighted | |
|------------|----------------|----------------|----------------|----------------|
| | α_5 | α_7 | α_5 | α_7 |
| Low | 0.16 | 0.19 | 0.33 | 0.34 |
| 2 | 0.12 | 0.14 | 0.44 | 0.44 |
| 3 | 0.18 | 0.21 | 0.26 | 0.28 |
| 4 | 0.28 | 0.31 | 0.41 | 0.39 |
| High | 0.59 | 0.61 | 0.70 | 0.66 |
| High – Low | 0.43 (5.53) | 0.42 (5.39) | 0.37 (2.31) | 0.32 (2.06) |

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

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

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

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

Table 2. 11: Alpha Estimates for Emotion Beta Sorted Portfolios: Robustness Tests

The table reports emotion premium across different subsample of stocks, alternative measures to generate market emotion index (MEI), and emotion valency-based approaches. In Panel A, we compute alpha after adjusting for microcaps, then we also estimate alphas for stocks included in the S&P 500 index, largest 1000 stocks, and based on Amihud's illiquidity measure most liquid 1000 stocks. For each month, we form quintile portfolios by sorting the subsampled stocks based on their emotion beta (β^{MEI}), where quintile 1(5) contains stocks with the lowest (highest) β^{MEI} during the previous month. For microcaps, we use the definition of Ball et al. (2020) and consider all but microcap stocks with market values of equity above the 20th percentile of the market capitalization. The columns report alphas (α_7) for value-weighted portfolios. The α_7 is the alpha relative to the market, size, value, momentum, profitability, investment, and liquidity factors. Panel B reports emotion premium (α_7) for alternative market emotion indices. First, we standardize MEI. Second, we use a time weight where MEI at day d receives more weight than MEI of day $d-1$. Thus, we compute the monthly MEI by weighting daily MEI by their respective time-weights ($Time\text{-}weighted\ MEI_t = \sum_{d=1}^t MEI_d \times weight_d$). Third, 'Total MEI' is calculated as the ratio of sum of excitement and anxiety words to total words in a month ($Total\ MEI_t = \frac{Excitement_t + Anxiety_t}{Total\ Words_t}$). Fourth, 'Net MEI' is calculated as the ratio of the difference between excitement and anxiety words to total words in a month ($Net\ MEI_t = \frac{Excitement_t - Anxiety_t}{Total\ Words_t}$). In Panel C, we form portfolios based on above and below median of rolling asymmetric emotion beta (β^{MEI}). We also report alpha (α_7) estimates for portfolios sorted on excitement beta and anxiety beta. To generate excitement and anxiety beta we estimate equation (2) using excitement and anxiety separately. The last row in each panel presents the differences between high and low portfolios. The t -statistics are computed after adjusting for Newey-West (1987) standard errors and are reported in brackets below the estimates. The estimation period is from January 1995 to December 2018.

| Panel A: Emotion premium across different stock subsamples | | | | |
|---|--------------------------|-------------------|----------------|----------------|
| Portfolios | Microcaps adjusted | S&P 500 | Largest 1000 | Liquid 1000 |
| Low | 0.46 | 0.44 | 0.46 | 0.51 |
| 2 | 0.18 | 0.24 | 0.25 | 0.22 |
| 3 | 0.41 | 0.32 | 0.33 | 0.34 |
| 4 | 0.27 | 0.36 | 0.23 | 0.24 |
| High | 0.84 | 0.89 | 0.88 | 0.90 |
| High – Low | 0.38 (2.39) | 0.45 (2.58) | 0.42 (2.70) | 0.39 (2.41) |
| Panel B: Alternative market emotion index (MEI) based emotion premium | | | | |
| Portfolios | Standardized MEI | Time weighted MEI | Total MEI | Net MEI |
| Low | 0.35 | 0.44 | 0.23 | 0.30 |
| 2 | 0.30 | 0.29 | 0.34 | 0.38 |
| 3 | 0.42 | 0.28 | 0.35 | 0.32 |
| 4 | 0.24 | 0.34 | 0.42 | 0.44 |
| High | 0.98 | 0.99 | 1.09 | 0.81 |
| High – Low | 0.63 (3.68) | 0.55 (3.38) | 0.86 (4.11) | 0.51 (2.86) |
| Panel C: Emotional valency-based emotion premium | | | | |
| Portfolios | Asymmetric β^{MEI} | | Emotions | |
| | Above median | Below median | Excitement | Anxiety |
| Low | 0.42 | 0.42 | 0.35 | 0.31 |
| 2 | 0.36 | 0.22 | 0.29 | 0.29 |
| 3 | 0.35 | 0.17 | 0.25 | 0.34 |
| 4 | 0.66 | 0.29 | 0.45 | 0.48 |
| High | 0.98 | 0.87 | 1.05 | 0.95 |
| High – Low | 0.56 (2.43) | 0.45 (2.17) | 0.70 (3.85) | 0.64 (3.73) |

Chapter 3

Emotional Exuberance and Local Return Predictability¹

3.1 Introduction

Emotions influence decision-making in a predictable and parsimonious way. The role emotions play in financial decision-making is becoming increasingly recognized in the empirical finance literature.² Recent mainstream return predictability studies focus on incidental emotions, such as mood, weather, sports sentiment, and music, in explaining future stock returns (e.g., Hirshleifer, Jiang, and DiGiovanni, 2020; Edmans et al., 2021; Obaid and Pukthuanthong, 2021). However, Lerner et al. (2015) show that integral or fundamental emotions, such as excitement and anxiety, are more powerful and have incremental ability to influence decision-making. In this paper, we examine the influence of excitement and anxiety on future stock returns at a local level. We investigate how local investors' emotional engagement with the stock market as reflected in local media reinforces their attachment to the stocks they invest in, and leads to predictable patterns in stock returns. Specifically, we introduce a novel 'emotional exuberance' measure, drawn from psychological theory to measure the psychological relationship investors have with the stock market. This dynamic and ambivalent emotional

¹ This chapter is based on a research paper jointly authored with Alok Kumar and Richard Taffler.

² Extant literature shows that psychological factors are related to financial markets. Saunders (1993) finds that local weather-induced mood affects stock prices. Hirshleifer and Shumway (2003) explore the impact of sunshine on people's mood and provide evidence that sunshine is strongly correlated with stock returns. Kamstra, Kramer, and Levi (2000) demonstrate that the impact of daylight-saving time change on sleep patterns magnifies the regular weekend effect on stock markets. They also provide evidence that stock market returns vary seasonally with the length of the day widely known as the seasonal affective disorder (SAD) effect (Kamstra, Kramer, and Levi, 2003). Edmans, Garcia, and Norli (2007) drawing on the link between sports outcomes and mood find market returns drop after soccer losses. Also, market-wide narrative pessimism puts downward pressure on market returns (Tetlock, 2007).

relationship, which psychologists refer to as an ‘object relation’ has important implications for local return predictability.

The extant literature on geography and stock prices shows how investors tend to invest more in local stocks for familiarity reasons known as the home bias puzzle (e.g., Coval and Moskowitz, 1999; Huberman 2001; Van Nieuwerburgh and Veldkamp, 2009; Solnik and Zuo, 2017). In addition, local investors’ ambivalent object relationships with local stocks we argue will also be reflected in their portfolio decisions. Our key conjecture is that local stock returns will vary with local emotional exuberance about the stock market, as manifest in local media, in a predictable manner. To the best of our knowledge, no previous study has tested the emotional drivers of stock return predictability empirically at the local level.

We resort to emotions in decision-making and object relations theory to explain investors’ psychological relationships with their investments. Lerner et al. (2015) show how integral emotions directly enter into the decision-making process, and are outside the scope of the rational choice model. Object relations theory describes the attachment that we all develop and experience nonconsciously with ‘objects’ such as people, ideas, or things derived from earliest infant experiences (see Auchincloss and Samberg, 2012). Investors enter into the same nonconscious relationships with their investments that go beyond their risk and return characteristics. Specifically, we posit that when local investors’ emotional exuberance, as measured by their level of excitement minus anxiety is positive, they invest more in local stocks and expect higher returns. When investor anxiety dominates excitement, we predict future local stock returns will fall. In this paper, we tease out these emotional dynamics and examine their ability to influence local investors’ portfolio decisions and future stock returns in addition to familiarity and local bias.

In constructing our local investor emotional exuberance measure, we work with local media. This is a valuable channel of information for investors (e.g., Dyck, Volchkova, and Zingales, 2008; Heese, Perez-Cavazos, and Peter, 2021). Local media outlet coverage influences how local investors feel about the stocks being reported on as manifested in its causal impact on local investor trading activity and firm value (Engelberg and Parsons, 2011; Gurun and Butler, 2012). Investor emotional exuberance about the stock market will also vary at the local level for at least two reasons. First, the views presented in (local) newspapers influence the assessments and estimations of individuals and institutional investors alike (see, for example, Goetzmann, Kim, and Shiller, 2016). Second, emotions vary because of the

differences in socioeconomic characteristics and psychological cultural makeup of individuals (Ekman et al., 1987; Matsumoto, 1993). Thus, because of investors' stronger object relationships with local stocks, these feelings of excitement and anxiety will create variation in investor behavior at the local level over and above the effects of geographical proximity.

Investors, both consciously and nonconsciously, engage more with local firms for several reasons. First, local firms are much more real and visible than distant out-of-state firms. Second, local investors know more about local firms compared to non-locals (Coval and Moskowitz, 1999). Third, local firms protect communities from adverse economic shocks such as reduction in employment (Kolko and Neumark, 2010), and also contribute to the local community directly, e.g., donations to educational institutions, hospitals, and charities. Finally, investors feel more connected to, and identified with, their local firms through word-of-mouth (Hong, Kubik, and Stein, 2005), and while socializing (Hong, Kubik, and Stein, 2004) with friends and family who work for local firms. Therefore, it is reasonable to assert that investors enter into stronger object relations with their local stocks that may drive their investment behavior, paving the way to local return predictability.

Kuhnen and Knutson (2011) show that the characteristics of markets have an impact on our emotional brain and may influence decision-making by altering risk preferences, and learning processes. We measure the emotional relationship of investors with the stock market as proxied by the Standard and Poor 500 index at the regional-level, and develop a local-level market emotion index. In spirit, we follow Hong, Kubik, and Stein (2008) who show that substantial local bias is prevalent at the Census region level. We measure local investors' emotional exuberance in terms of their levels of excitement and anxiety about the state of the stock market as conveyed in local media. We use market-level local news as this is likely to be more salient in the minds of local investors, and media comment more generally is often used as a reference point (see Shiller, 2017) to evaluate/compare current market performance. Market-wide news is also more available compared to firm-level news.

We utilize local newspaper media to construct our market emotion index, which measures investor emotional exuberance, for several reasons. First, media plays the role of an external monitor (Dyck, Volchkova, and Zingales, 2008; Heese, Perez-Cavazos, and Peter, 2021), thereby shaping investors' emotional relationships with the stock market and their investments. Based on the nature of their emotional attachment with the stock market which we proxy here by the emotions of excitement and anxiety, investors' decision-making varies.

Thus, how local newspapers write about the stock market should dynamically impact investors' expectations about future local stock returns. Second, the local media publish stories specifically catering to the interest of local investors. Gurun and Butler (2012) term the local press 'cheerleaders' as they create 'hype' about local stocks. Stock market participants draw on information from the local media in making investment decisions and such hype can be viewed as a deviation from rationality. Therefore, we hypothesize that levels of emotional exuberance as reflected in the local press should affect the market valuation of local stocks.

To test our local emotional exuberance and local return predictability conjecture, we define the 'geographic area' local to an investor. We use U.S. states as our geographical unit as data are available at state-level and previous research (e.g., Coval and Moskowitz, 1999, 2001; Korniotis and Kumar, 2013) uses state as the primary geographical unit. In line with the existing literature (e.g., Loughran and Schultz, 2005; Pirinsky and Wang, 2006; Hong, Kubik, and Stein, 2008), we form state-level portfolios using corporate headquarter location to proxy for firm location.

Our choice of the return predictor is guided both by studies exploring the relationship between investor emotions and asset prices, and object relations theory. Experimental studies of trading emotions and asset prices (see, for example, Breaban and Noussair, 2018) confirm the close association between emotions and market dynamics. An excited emotional state correlates with notional stock purchases and price increases (Andrade, Odean, and Lin, 2016), while anxiety and fear correlate with selling and price falls. However, most directly relevant to us is the recent study of Bin Hasan, Kumar, and Taffler (2021) which demonstrates empirically how investor anxiety and excitement about stocks directly influence their market pricing. This paper shows that through their emotional attachment to the stock market investors experience emotions such as excitement and anxiety from which they derive emotional exuberance.

Our emotional exuberance measure captures emotional-induced variation in investor preferences. Kuhnne and Knutson (2011) also show experimentally that excitement and anxiety are key investor emotions. In parallel, Bin Hasan et al. (2021) show that the integral emotions of anxiety and excitement are the most fundamental drivers of investor decision-making they explore. Psychologists point out how individual psychology constantly revolves around the search for excitement and the avoidance of anxiety (Tuckett and Taffler, 2012), and

in line this, we employ measures of investor excitement and anxiety to measure investor emotional exuberance-driven utility.³

We draw on local newspaper articles about the stock market to generate the excitement and anxiety word counts using the standard bag-of-words method. We define our market emotion index, which measures emotional exuberance, as the ratio of the difference between excitement and anxiety words to the total of excitement and anxiety words. The databases we use, Nexis and ProQuest, do not subscribe to each and every state-level newspaper, consequently we group available newspapers together at region level. Hong, Kubik, and Stein (2008) also provide evidence that the relationship between stock price and local bias is at the Census region level. The U.S. Census Bureau divides the U.S. into four regions – Northeast, Midwest, South, and West – based on socioeconomic homogeneity. We use this Census classification and count emotional words using regional media article word counts to proxy for state-level emotions and construct our emotional exuberance measure.

To ensure that our state-level emotional exuberance measure correctly predicts state portfolio returns we control for other well-established state-level return predictors. As controls we use Korniotis and Kumar's (2013) three state-level predictors, state income growth, state relative unemployment rate, and state housing collateral ratio in our return prediction models. Growth rate of labor income proxies for the return to human capital (Campbell, 1996; Jagannathan and Wang, 1996). Relative unemployment rate represents unemployment news. The final state-level predictor, the state housing collateral ratio, acts as a proxy for investors' borrowing constraints and their ability to share risk (Lustig and van Nieuwerburgh, 2005, 2010).

We also ensure that the predictable pattern we observe in state-based portfolio returns does not reflect aggregate U.S. stock market predictability by working with the state-specific or idiosyncratic component of state portfolio returns. We compute the idiosyncratic state-specific component using various factor models and return adjustment methods that also avoid look-ahead bias. We include several U.S.-level variables to ensure that emotional exuberance-driven predictability does not reflect broader shocks to the national economy. Further, we

³ Along with the utility of wealth investors derive emotional utility from making investment decisions. Investors' emotional engagement with the stock market and attachment to their stocks captures such utility. Caplin and Leahy (2001) develop a model of psychological expected utility that captures anticipatory feelings such as anxiety and show that an optimal strategy exists.

assess whether our emotional exuberance-driven predictability is distinct from the known effects of narrative tone, sentiment, local optimism, local macroeconomic news, and local bias. Finally, we also examine whether our regional market emotion index can predict future local returns in the presence of market-wide emotional exuberance and tone measures. Because if local emotional exuberance is important and affects local investors' investment decisions in a predictable manner, then it should be able to continue to do so after taking into account overall market emotions.

We test state portfolio return predictability by estimating panel fixed effects regressions using quarterly data for 1990 to 2018.⁴ Consistent with our main conjecture, we find that an increase in state emotional exuberance is associated with higher state portfolio returns in the next quarter. This predictability remains significant accounting for local narrative tone based on Loughran and McDonald (2011) and Henry (2008) positive negative word lists. Likewise, our novel emotion-based predictability measure differs from investor sentiment (Barker and Wurgler, 2006) and general consumer sentiment as measured by the University of Michigan's Consumer Confidence Index. Also, predictability survives when we control for local optimism as measured by the regional small business optimism index, and local macro-related information captured by the State Leading Index (SLI) of Crone and Clayton-Matthews (2005). Finally, we show that our emotional exuberance-driven predictability measure is not a repackaging of local bias as we control for Hong, Kubik, and Stein's (2008) local bias-based measure.

To measure the economic significance of our predictability regression estimates, we construct an emotional exuberance-driven geography-based trading strategy. This strategy exploits the predictable pattern we find in state portfolio returns. Through our research design, we ensure that our portfolio-based approach remains free from look-ahead bias, and accounts for the time-varying riskiness of state portfolios. Our trading strategy takes a long (short) position in state portfolios with the highest (lowest) predicted returns. Specifically, to rank state portfolios, we estimate our return prediction model recursively using only past data to predict next quarter's return. We find that our emotional exuberance-based geographic Long-Short portfolio generates an economically significant annualized alpha of 9.17% when we consider

⁴ Nexis and ProQuest databases mostly commence their coverage of the local newspapers we draw on in 1990.

a combination of Fama and French (1992, 2015) factors. This relationship is stronger for states in regions with high emotional exuberance.

Certain regions are more sensitive to the U.S. business cycle, meaning our results could reflect time variation in the risk exposures of local firms to U.S.-level systematic risk factors. To deal with this, we employ conditional factor models to account for the time-varying risk exposures of state portfolios. In addition, our trading strategy alpha is robust when we construct our emotional exuberance measure in different ways. Our results remain equally significant when we exclude state-level macroeconomic predictors.

We also test the robustness of our results after excluding financial, growth, low price, and small stocks. Our emotional exuberance-driven geography-based trading strategy still produces economically significant abnormal returns. Consistent with our prediction, we also find that mispricing is stronger among firms with lower visibility. Overall, our results show that local investors' feelings of excitement and anxiety about the stock market affect local mispricing in an economically meaningful way. This mispricing ameliorates over time becoming insignificant in about six months.

Taken together, our empirical results indicate that predictable patterns in state portfolio returns reflect mispricing generated by investors' ambivalent emotional relationships with the stock market taking into account the time-varying riskiness of state portfolios. Our findings support the emotions in decision-making and object relations-based psychological theories as applied to local stocks. Local investors derive emotional exuberance from the news conveyed in articles about the stock market and enter into intensified emotional relationships with local stocks which influence their portfolio decisions, and pave the way for return predictability.

Our main contribution is to demonstrate how investor integral emotions affect their investment decision-making and return predictability at a local level. We add to the studies on feelings and financial decisions that shows people in a more positive mood tend to be more risk tolerate and demand risky assets more (Bassi, Colacito, and Fulghieri, 2013; Kaplanski et al., 2015). Our research complements Bin Hasan et al. (2021) in going beyond merely experimental settings (e.g., Kuhnen and Kuntson, 2011; Andrade, Oden, and Lin, 2016; Breaban and Noussair, 2018) to real-world markets to shed more light on how investor emotions drive asset prices.

More broadly, we contribute to the local return predictability (Korniotis and Kumar, 2013; Smajlbegovic, 2019), and mood and aggregate economic outcomes literature (Chhaochharia et al., 2019; Chhaochharia, Korniotis, and Kumar, 2020). We show that our local emotional exuberance-driven measure complements local economic predictors in predicting future local stock returns. Extant research provides evidence of the relationship between news and stock market phenomena (see, for example, Tetlock, 2007; Tetlock et al., 2008; Gurun and Butler, 2012; Hillert, Jacobs, and Muller, 2014) and our paper also contributes to this dynamic news and finance literature.

Regardless of whether it is emotional exuberance that drives local return predictability, as we conjecture, this newly discovered predictability mechanism is important. We speculate investors' emotional engagement with the stock market and together with their attachment to local stocks may provide a plausible explanation for local return predictability that is otherwise difficult to explain using standard asset pricing theory.

The rest of the paper is organized as follows. In the next section, we describe the theoretical motivation for our return predictor. In section 3, we describe our data and present the empirical models used to examine return predictability. Section 4 reports our empirical findings on local return predictability using our state-level emotional exuberance measure. We conclude in section 5 with a brief discussion.

3.2 Theoretical Motivation and Testable Hypotheses

We draw on emotions in decision-making and object relations theory in psychology to derive our key economic intuition. The conceptual underpinning of our emotional exuberance measure is built on the idea that we are driven by the search for pleasure and avoidance of pain (or in psychological terms, the pleasure principle vs. the reality principle). The psychological literature provides evidence that emotion influences decision-making under conditions of risk and/or uncertainty (Zajonc, 1980; Lerner et al., 2015). Mehra and Sah (2002) show theoretically that fluctuations in mood in only a handful of investors, with limits to arbitrage, affect investors' subjective risk assessment parameters and impact equity prices accordingly. An emotional assessment of potential risks and rewards differs from rational evaluation when it comes to equity pricing (Loewenstein, 2000). Thus, emotions have the capability to influence economic behavior. In line with this argument, we introduce the concept of the emotional utility

investors derive from investing as captured by our emotional exuberance measure. This exuberance-driven emotional relationship with the stock market has pricing implications at the local level.

Investors develop ambivalent object relationships with stocks and attach emotional value to them which may even dominate their relative attractiveness measured in conventional rational (or risk/return) terms. According to object relations theory the existence of simultaneous ‘love’/‘hate’ feelings about an object (Auchincloss and Samberg, 2012) which we experience nonconsciously determines the way we relate to it. In this paper, we use excitement and anxiety to proxy for emotional ambivalence. Excited investors fuel stock prices and create an expectation of soaring returns. The selling pressure of anxious investors, on the contrary, drives down stock returns. The whole process is exacerbated when investors feel emotional proximity to local stocks consciously (either by socialization or word-of-mouth) or nonconsciously (object relations). In this paper, we recognize this “emotion-object relation-expectation-action” process and test this conjecture empirically.

To develop our key hypotheses, we assume that there is a representative investor for each U.S. state. By reading favorable or unfavorable news about the stock market in the local press, the emotional love/hate relationship this notional investor has with the stocks he/she is particularly emotionally engaged with, i.e., in our case local stocks, becomes stronger. Specifically, if investors feel excited about the stock market and derive positive emotional utility from it, our representative state investor is likely to invest more in local stocks driving their prices up and creating the possibility of higher future stock returns. On the contrary, if the local press reflects anxiety about the stock market, then investors will sell their emotionally proximate local stocks lowering near term future stock returns. Thus, if local investors’ excitement dominates their anxiety as measured by their emotional exuberance, then local stock returns will increase at least in the short-term, *ceteris paribus*, and conversely. This assertion leads to our first hypothesis:

Hypothesis 1: Local investor emotional exuberance predicts local stock returns.

We propose that investors’ emotional relationships with the stock market as measured by state-level emotional exuberance help drive local investment and portfolio choices. Because emotions i.e., emotional valence, affects economic decision-making (see Lerner et al., 2015), we focus on the impact of excitement and anxiety in evaluating signals about likely state

portfolio returns. Emotional valence results in variations in factor and stock-specific mispricing and, consequently, leads to return predictability (see Hirshleifer, Jiang, and DiGiovanni, 2020).

Korniotis and Kumar (2013) show that investors try to utilize the predictable pattern in local stock returns by forming state-level long and short portfolios. If investor emotion correctly predicts local stock returns, then an emotion-driven trading strategy based on geography will lead to abnormal state portfolio performance. This notion provides us with the foundation for our next hypothesis:

Hypothesis 2: Higher local emotional exuberance leads to higher abnormal state portfolio return.

Empirically, if emotional exuberance is reasonably stable over time, high emotional exuberance state portfolios (Long) predicted to have high returns next quarter will outperform low emotional exuberance state portfolios (Short) predicted to have low returns during subsequent periods when such exuberance is high. Conversely, the Long-Short portfolio will underperform when emotional exuberance is low. Thus, we expect high emotional exuberance to lead to higher abnormal state portfolio returns.

Our emotional exuberance measure utilizes the variations in investors' integral emotions. Integral emotions of excitement and anxiety are inherently different from incidental emotions such as mood and sentiment (see Lerner et. al., 2015). Also, we expect investors to derive additional emotional exuberance-driven utility by investing in their local stocks apart from reasons such as the local bias. Caplin and Leahy (2001) show that individuals maximize their psychological expected utility, and we speculate this utility drives local investors' decision-making. Thus, we believe our emotion measure captures a local return predictability mechanism that is distinct, and this leads to our final hypothesis:

Hypothesis 3: Integral local emotional exuberance-driven return predictability is distinct and complementary to standard pricing effects.

Overall, we conjecture that when local emotional exuberance is high investors react by entering into object relationships with local stocks and expect higher stock returns. This emotional exuberance leads to a predictable pattern in local stock returns. Specifically, through the lens of emotional exuberance-driven utility investors find local stocks to have extra

‘emotional glitter’ that is distinct from non-local stocks that affects their decision-making and expectation of future stock returns.

3.3 Data and Methodology

This section describes the different data we use to measure emotional exuberance, stock-level data, state and U.S.-level predictive variables, and methods for assessing local stock return predictability. Analysis covers the period from January 1990 to December 2018.

3.3.1 News Data

It is challenging to measure and quantify emotion. Newspaper articles as a medium help form perception (Shiller, 2015) so are an ideal candidate for quantifying emotion. However, newspapers do not follow every firm listed in the three major U.S. stock exchanges (NYSE, AMEX, and NASDAQ). Hillert, Jacobs, and Muller (2014) find the median number of articles published in a given year by the national media about a firm is only three. Most importantly, newspaper media covers less than half of the U.S. stock market considering at least one article about a firm per year. Such lack of general coverage, therefore, poses a considerable barrier in forming a dataset with a good amount of time and cross-sectional variation at the individual stock level. Consequently, we collect news items about the S&P 500 index which the media reports extensively over a long period and apply content analysis methods to construct our emotional exuberance measure.

We collect 64,278 news articles from the wide range of newspapers listed in Table 3.A.1 with associated number of articles. Newspapers are divided into four U.S. Census regions. Census region classification is provided by the U.S. Census Bureau.⁵ Socioeconomic homogeneity is the principal criterion employed in grouping states into regions.⁶ We use regional newspapers as a proxy for state-level newspapers. Hong, Kubik, and Stein (2008) argue that regional-level local bias is more appropriate for assessing the impact on stock prices because it better reflects the total incremental demand for a stock induced by local bias. There is also the concern that some of the newspapers we work with are national rather than local

⁵ https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf

⁶ <https://www2.census.gov/geo/pdfs/reference/GARM/Ch6GARM.pdf>

(e.g., The Wall Street Journal). However, we believe that the emphasis and attention local readers put on news stories published in their area, though these are national, would be significantly higher than non-local readers. Nonetheless, if this is an issue then it can only work against us identifying an emotional exuberance-driven predictability mechanism.

In our sample, the Northeast, Midwest, and South regions each have 13 newspapers. The West region has the least number of newspapers (8). The largest states by population are California, Texas, and New York. For robustness tests, we exclude the largest states in our predictability regressions. Large companies such as Walmart in Arkansas, and Microsoft and Amazon in Washington state, dominate a state's activities. In robustness checks, we also exclude dominating firm states from our predictability regressions to ensure that the predictability we observe is not driven by such states.

Table 3.A.1 also displays the list of newspapers, availability, regions, and articles by each newspaper. News articles are sourced from the Nexis and ProQuest databases. To identify index-specific news, we use the "relevance score" measure of Nexis. For baseline tests, we retain all articles with a relevance score of equal or more than 80%. We exclude newswires, non-business news, and websites. To gather index-specific news, we use 'Stock Index', 'S&P 500', and 'Stock Market' jointly as keywords in the power search function. ProQuest, on the other hand, does not provide any relevance score for index-specific articles, rather it sorts articles by relevance. In this case, to alleviate the problem of gathering articles that are not index-specific or may relate to other economic news at the same time we include the same search term mentioned above and require the search terms to be present in the abstract, headline, and main text. All the Wall Street Journal articles are from ProQuest; Nexis covers the rest of our newspapers. Both databases have variable coverage across all newspapers from 1990 motivating our study period to be from January 1990 to December 2018.

3.3.2 Return Data

We investigate the relationship between regional market-level emotional exuberance and local stock returns by estimating quarterly return prediction models. The dependent variable in the return prediction model is the next-quarter return of a value-weighted state portfolio of firms headquartered in a U.S. state. Monthly stock returns data are from the Center for Research in Security Prices (CRSP). Analysis only uses common stocks with share codes 10 and 11 listed on the NYSE, AMEX, and NASDAQ. In the case of missing returns, we use delisting returns.

We follow the local bias literature (e.g., Coval and Moskowitz, 1999, 2001; Loughran and Schultz, 2005; Hong, Kubik, and Stein, 2008; Korniotis and Kumar, 2013) and use corporate headquarters locations to proxy for firm location. Firm headquarter location data are from COMPUSTAT. Following Korniotis and Kumar (2013) we exclude states with less than 15 firms to minimize measurement error.

Our return prediction model uses the idiosyncratic component of state portfolio returns. This ensures that state portfolio returns are orthogonal to the aggregate U.S. stock market. The predictability regression dependent variable captures the state-specific components of returns. We also use various factor models and return adjustment methods to compute the state-specific component of returns. Our main tests use return adjustment methods that are free from look-ahead bias, and allow us to perform out-of-sample tests of return predictability.

We estimate our factor models using full-sample data to minimize estimation error. However, this approach introduces look-ahead bias. To avoid this bias, we follow Korniotis and Kumar (2013) and define residual returns using two performance benchmarks. The first state-specific return measure is the characteristic-adjusted return following Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) method. In the second, we use industry-adjusted return where industry is defined by the Fama-French (1997) 38-industry classification.

We use quarterly returns in our empirical analysis as the state-level control variables are available only at quarterly frequency. State-level control variables are mainly macroeconomic variables that are well known to have local return predictability. Nominal returns are divided by one plus the inflation rate to obtain real returns. Inflation rate is obtained from CRSP. We also use value-weighted quarterly market returns available from CRSP. Quarterly risk-free rates are computed using monthly 30-day Treasury bill rates.

3.3.3 State- and U.S.-level Business Cycle Data

Korniotis and Kumar (2013) find that local stock returns vary with local business cycles. They provide evidence that state portfolios earn higher future returns when state-level unemployment rates are high and housing collateral ratios are low. We use their state-level macroeconomic indicators as control variables to test our conjecture that local investor emotional exuberance can predict local future stock returns.

The three state-level economic indicators we employ are the growth rate of state labor income, the relative state unemployment rate, and the housing collateral ratio (see Korniotis and Kumar, 2013). State-level labor income data are obtained from the Bureau of Economic Analysis (BEA) and state-level unemployment data are from the Bureau of Labor Statistics (BLS). We follow the same definitions as Korniotis and Kumar (2013) to construct state-level predictors. State-level income growth is defined as the log difference between state income in a given quarter and state income in the same quarter in the previous year. This measure is used to proxy for the return to human capital (e.g., Campbell, 1996). The relative state unemployment rate is the ratio of the current state unemployment rate to the moving average of state unemployment rates over the previous 16 quarters. The relative state unemployment rate measures innovations in unemployment, and is a recession indicator for the state economy. The housing collateral ratio is the log ratio of housing equity to labor income, and is denoted by hy . Following Korniotis and Kumar (2013), we construct the state-level housing collateral ratio using the Lustig and van Nieuwerburgh (2005) method. The state-level housing collateral ratio indicates borrowing constraints, and variation in the degree of risk-sharing across U.S. states.

We also use dividend-price ratio of state portfolios (e.g., Campbell and Shiller, 1988; Fama and French, 1988). The quarterly dividend-price ratio is the log of one plus the quarterly dividend-price ratio (D/P), and for a state portfolio the D/P is the value-weighted D/P of firms headquartered in the state. Here, D is the sum of the previous four quarterly dividends, and P is the end-of-month stock price as defined by Korniotis and Kumar (2013). Monthly stock prices are from CRSP, and quarterly dividends at stock-level are from COMPUSTAT.

We also control for U.S.-level macroeconomic variables because if state portfolio returns are correlated with the aggregate stock market, and if state predictors are correlated with U.S.-level indicators, the predictability of state portfolio returns could simply reflect the predictability of aggregate stock market indices. We use several U.S.-level indicators. Specifically, we use the *cay* residual of Lettau and Ludvigson (2001a, 2001b), the housing collateral ratio of Lustig and van Nieuwerburgh (2005), the growth rate of labor income, the relative unemployment rate, the paper-bill spread (the difference between 30-day commercial paper and 30-day Treasury bill), the term spread (the difference between a 10-year government bond and a 1-year government bond), the default spread (difference between a Baa corporate bond and a 1-year government bond), the investor sentiment measure of Baker and Wurgler

(2006), and the University of Michigan's Consumer Confidence Index. All these U.S.-level indicators can predict aggregate stock market indices. The three return spreads data, and consumer confidence index are from the Federal Reserve Bank of St. Louis.⁷ Investor sentiment data is from Jeffrey Wurgler's website.⁸

3.3.4 Factor Data

For factor models, we collect the Fama and French factor data, risk-free rate, and industry classification data from Kenneth French's data library.⁹ The Fama and French factor data includes excess market returns (RMRF), small-minus-big (SMB), high-minus-low (HML), winners-minus-losers (UMD), short- and long-term reversals (STR and LTR), robust-minus-weak (RMW), and conservative-minus-aggressive (CMA) factors. The liquidity factor (LIQ) is from Lubos Pastor's data library.¹⁰

3.3.5 State Demographics

We also collect state demographic information from the Census survey. Census data relating to state population (TOTPOP) are available only at decade level but provides yearly estimates. The U.S. Census survey also provides yearly estimates of different state demographics such as median age of state residents (M_AGE), proportion of state residents over age 25 with a bachelor's degree or higher (EDU), male-female ratio (MALE), proportion of married residents (MARRIED), proportion of state residents who are non-white (MINORITY), proportion of state residents living in urban areas (URBAN), average income of residents (INCOME), and proportion of poor (POVERTY) residents. We interpolate the demographic information to compute quarterly proxies for state-level demographic variables.

3.3.6 Estimating Emotional Exuberance

We estimate state-level investor emotional exuberance by constructing a local-level market emotion index using the bag-of-words technique. There are a dearth of readily available off-the-shelf emotion word dictionaries. Taffler et al. (2021) develop keyword dictionaries to

⁷ <https://fred.stlouisfed.org/series/UMCSENT>

⁸ <http://people.stern.nyu.edu/jwurgler/>

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

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

reflect investor emotions. Tuckett and Taffler (2008) explain different stages of asset prices that evoke different emotions. The categories of emotions are ‘Excitement’, ‘Anxiety’, ‘Mania’, ‘Panic’, ‘Blame’, ‘Denial’ and ‘Guilt’. The dictionaries include 835 words. Dictionary development is based on media reports published in widely circulated daily U.S. newspapers during dot.com mania when investor emotions were very salient, and supplemented using Harvard IV-4 GI and Lasswell Value keyword dictionaries. Important human emotion words from the Book of Human Emotions (Watt-Smith, 2015) further enrich their dictionaries. The authors employ extensive keyword-in-context (KWIC) analysis to ensure that the words included in their final dictionaries have emotional content. Bin Hasan et al. (2021) shows that Taffler et al.’s (2021) excitement- and anxiety-based dictionaries equally capture emotions during general market conditions, and that these are priced. Taffler et al. (2021) also offers out-of-sample validity by testing their emotion word dictionaries during the Global Financial Crisis. Both Taffler et al. (2021) and Bin Hasan et al. (2021) provide detailed descriptions of the dictionary development process.

Schmeling and Wagner (2019) point out several benefits of using off-the-shelf dictionaries. First, relying on a well-established dictionary to classify words avoids the need for a subjective classification of words. Alternatively, developing dictionaries either by just selecting words based on common sense or based on algorithmic procedures create bias in the wordlist potentially affecting the empirical analysis. In addition, using a statistical procedure requires using the same data twice, first to classify words, and second, to analyze the effect on asset prices, leading to hindsight bias. Although one might obviate the need to use the same data twice by dividing the data into training and test sets, this would significantly reduce the sample period. Therefore, employing the Taffler et al. (2021) emotion dictionaries in this study seems a reasonable approach and, in any case, our study also provides further empirical evidence of their validity out of sample. Following Henry and Leone (2016), we define our state-level market emotion index, which measures local investors’ emotional exuberance, as follows:

$$MEI_{j,t} = \frac{Excitement_{j,t} - Anxiety_{j,t}}{Excitement_{j,t} + Anxiety_{j,t}} \quad (1)$$

where, $MEI_{j,t}$ is the market emotion index of state j in quarter t . $Excitement_{j,t}$ and $Anxiety_{j,t}$ are the number of excitement and anxiety words in the local news articles relative to the total number of words in local news articles for state j in quarter t . It is difficult to collect

the newspaper articles for each individual U.S. state over a long period mainly because the Nexis and/or ProQuest database do not subscribe to all of a state's newspapers. Therefore, we use newspaper articles at the regional level, and proxy state-level MEI by region-level MEI.

Bin Hasan et al. (2021) provide evidence that the Taffler et al. (2021) emotion keyword dictionaries are also work beyond the dot.com bubble period. We also perform validation tests discussed in the next subsection which imply that the emotion dictionaries we use are appropriate for identifying and capturing dynamic investor emotions. Further, in Appendix Table 3.A.3 Panel B, we show that our local emotional exuberance measure has low correlations with investor sentiment and the consumer confidence index providing initial evidence that our measure is capturing additional information left untapped. Following chapter 2, we also employ a market-level emotion index and examine the power of local emotional exuberance-driven predictability controlling for the overall market emotion index.

We generate emotion word counts based on keyword dictionaries and normalize them by taking proportions. Loughran and McDonald (2011) also use a simple proportion of words for a given tone classification. Application of more complex procedures such as term weighting and topic modeling would imply hindsight bias, and offers trivial improvement (Henry and Leone, 2016).

We do not use the Loughran and McDonald (2011) (LM) positive-negative dictionary words directly for two reasons. First, their positive-negative dictionary is developed on the basis of 10-K reports that are full of accounting and/or financial jargon, and Lawrence (2013) suggests that investors invest more in firms with annual reports containing fewer words and better readability. Second, this dictionary is not emotional context-specific. Thus, we follow the advice of Henry and Leone (2016) who argue for the use of domain-specific word lists. However, we control for both LM's positive-negative tone and Henry's (2008) (HN) positive-negative tone in our robustness tests.

3.3.7 Validation Tests: Are We Capturing Emotional Exuberance or Something Else?

We use an indirect approach to capture investor emotions as opposed to examining human reactions such as facial expressions using facial recognition software. Experimental studies use different kinds of technology to capture subjects' emotional reaction (see, for example, Kuhnen

and Knutson, 2011; Andrade, Odean, and Lin, 2016; Breaban and Noussair, 2018). We, however, try to capture the emotions investors experience in real-world financial markets. To do so, we count emotional words reflecting emotions in newspaper articles. There are two broad concerns related to our approach. First, are the emotional keyword dictionaries we use to construct our emotional measure meaningful and valid? Second, are the news articles we use capturing macroeconomic news or surprises whether local or national? We dissect these issues next.

In the first case, we show that Taffler et al.'s (2021) excitement- and anxiety-related emotional keyword dictionaries also appropriately classify these emotions at the local level, and Bin Hasan et al. (2021) show that they influence investors' portfolio decisions during normal market conditions at the individual stock level. Nyman, Kapadia, and Tuckett (2021) and Tuckett, Smith, and Nyman (2014) narrow down the Loughran and McDonald (2011) positive and negative word lists to compile a parallel excitement- and anxiety-related word dictionaries which they use to assess sentiment shifts prior to the financial crisis. We construct our local market emotion index using their word lists, we find that this correlates on average across Census regions at the 0.59 (p -value = 0.00) level with our base measure.¹¹ Despite the very different basis of dictionary construction this moderate-to-high correlation helps us reasonably to assert that we are capturing excitement and anxiety.

Our approach to tracking local investor emotions may also raise other questions such as that instead of capturing emotions we may be simply picking up local macroeconomic surprises. We seek to alleviate concerns about this issue in several ways. First, we try to make sure we collect only stock market and S&P 500 index-related news in our search processes. Second, we follow Nyman et al. (2021) in excluding macroeconomic-related words and find resulting local market emotion index correlates with our base measure at 0.99 (p -value = 0.00) level across Census regions.¹² Finally, in our predictability regressions we control for several state-level macro predictors that capture the local macroeconomic environment such as state-

¹¹ We thank Rickard Nyman for supplying us with the word lists. Table 3.A.2 provides detailed correlation coefficients.

¹² In addition to Nyman et al.'s (2021) 'boost', 'boosts', and 'boosted' words, we also from our excitement dictionary exclude 'boosting', 'booster', 'expand', 'expands', 'expanding', 'expanded', and 'expansion'. Likewise, we exclude 'shrink', 'shrinks', 'shrinking', 'shrunk', and 'shrinkage' from the anxiety word lists in addition to Nyman et al.'s (2021) 'uncertain' and 'uncertainty' word exclusions which Baker, Bloom, and Davis (2016) also use while developing their economic policy uncertainty index. See Table 3.A.2 for correlations across these measures.

level income growth, state relative unemployment rate, state housing collateral ratio, state-level economic forecast proxied by the State Leading Index, and the state economic activity index of Korniotis and Kumar (2013). Thus, we believe our emotional exuberance measure is not capturing local macro-level news and surprises.

We also check whether our emotional exuberance measure is closely related to sentiment. The correlations between our measure and the Baker and Wurgler (2006) sentiment index and University of Michigan's Consumer Confidence Index are low across the US Census regions. For robustness, we also include these as controls in our prediction model. As these sentiment measures are available only at market level, additionally we control for local optimism levels as measured by the regional small business managers optimism index.¹³

Taken together, we acknowledge the challenges in tracking investor emotions and do not consider ours' is an ideal measure. However, we make every attempt to eliminate issues that could raise concerns regarding the validity of our emotional exuberance measure.

3.3.8 Specification of Return Predictability Regression

We estimate one-quarter ahead predictability regressions. We pool observations from all states and express our return prediction model as a panel regression specification to increase the power of statistical tests. Following Korniotis and Kumar (2013), we predict quarterly state portfolio return in quarter t using the lagged local market emotion index, and state and U.S.-level macroeconomic predictors in quarters $t - 1$ or $t - 2$:

$$Y_{j,t} = \alpha_j + X_{j,t-1}^{MEI} \delta_1 + X_{j,t-2} \delta_2 + X_{USA,t-2} \delta_3 + \log(1 + D/P)_{j,t-1} \delta_4 + \varepsilon_{j,t} \quad (2)$$

where, $Y_{j,t}$ is the residual or state-specific return of state portfolio j in quarter t . The term α_j is the state-specific mean and captures unobserved differences in the returns of state portfolios. Vector $X_{j,t-1}^{MEI}$ contains state-level MEI. State-level MEI is measured in quarter $t - 1$. The vector $\delta_{1,MEI}$ includes coefficient estimates of state-level MEI. Row vector $X_{j,t-2}$ includes state-level macroeconomic return predictors measured in quarter $t - 2$. The row vector δ_2 contains coefficient estimates for relative state income growth, relative state unemployment rate, and state-level housing collateral ratio. Row vector $X_{USA,t-2}$ contains the aggregate U.S.-

¹³ The small business optimism index is available at <http://www.nfib-sbet.org/indicators/>.

level predictors that are measured in quarter $t - 2$ as macroeconomic predictors are usually reported with a lag of two quarters. $\log(1 + D/P)_{j,t-1}$ is the log of one plus the dividend-price ratio for state j in quarter $t - 1$. δ_3 and δ_4 contain the coefficients of U.S.-level predictors and state-level dividend yield. Finally, $\varepsilon_{j,t}$ is the regression error term.

We estimate our pooled panel regression with state and year fixed effects using the ordinary least squares (OLS) method. We compute t -statistics using Driscoll and Kraay (1998) standard errors to adjust for serial correlations in our panel structure. The coefficient estimate $\delta_{1,MEI}$ measures the responsiveness of state portfolio returns to changes in state-level emotional exuberance after controlling for state- and U.S.-level return predictors. Our key hypothesis is that an increase in state emotional exuberance reflected in regional newspaper articles about the stock market is followed by higher state portfolio returns. We test the hypothesis using the following one-sided predictability test:

$$H_0: \delta_{1,MEI} = 0; H_A: \delta_{1,MEI} > 0 \quad (3)$$

3.4 Empirical Findings and Discussion

In this section, we assess the ability of the state-level market emotion index, which measures local investors emotional exuberance-driven utility, to predict future local stock returns. First, we present descriptive statistics. Second, we discuss our return predictability regression results, and construct emotional exuberance-driven geography-based trading strategies. Third, we report out-of-sample tests, and examine abnormal returns in the longer horizon. Fourth, we check the demographics of states included in our hedge portfolios, and link these with the state emotional exuberance measure. Fifth, we explore whether emotional exuberance is distinct from known local pricing factors. Finally, we provide evidence from robustness checks.

Panel A of Table 3.1 presents summary statistics for quarterly state returns and all state- and U.S.-level return predictors.¹⁴ State-level market emotion index is reported with a lag of one quarter. State- and U.S.-level macroeconomic predictors are reported with a lag of two quarters, and all other variables are reported with a lag of one quarter. Nominal measures for all variables are transformed into real terms using regional inflation rates from the BLS. The

¹⁴ We also present summary statistics of local MEI across the U.S. geographic regions in Panel A of Table 3A.3. On average, local MEI is similar in magnitude across all four U.S. Census regions with the West region having higher volatility in local market emotions.

inflation index base year is 1990(Q1). As can be seen, state quarterly portfolio return (R_{local}) is 1.439 with a standard deviation of 0.066 which is very similar to Korniotis and Kumar (2013). State-level emotion and tone measures are less volatile and less autocorrelated than state-level macroeconomic return predictors. U.S.-level counterparts are more autocorrelated than state-level predictors.

Panel B of Table 3.1 provides summary state demographics statistics which influence the way residents treat local news stories (e.g., Kim et al., 2021). Mean state resident age is 36.2 years. One-quarter of state residents are over 25 years of age with a bachelor or higher degree. The male to female ratio is 0.969, and half of the residents are married. One-fifth of residents are non-white, and 73% of residents live in urban areas. Approximately 13% of residents are living in poverty. States with proportionately more educated and high-income residents are likely to exhibit stronger emotional relationships with the stock market as reflected in local newspapers due to their demographic profile. Goetzmann, Kim, and Shiller (2016) find that high income Americans have exaggerated feelings, i.e., anxieties, about a potential stock market crash, and such feelings are influenced by front page news. Moreover, investors in high-income states are likely to participate more in the stock market. We speculate these demographic differences are likely to have important implications for return predictability.

We also explore the relationship between state portfolio returns, state-level market emotion index, tone measures, and state- and U.S.-level macroeconomic variables.¹⁵ Table 3.2 reports the results of Spearman rank correlations. Most importantly, state portfolio return is positively correlated with emotional exuberance as measured by the market emotion index. This reflects how increased excitement (anxiety) about the stock market leads investors to invest (disinvest) heavily in local stock portfolios to earn (avoid) higher (lower) future returns. The state-level market emotion index is also correlated with other state- and U.S.-level return predictors. We include U.S.-level variables in our empirical analysis to ensure that state-level predictors only capture state-specific shocks.

¹⁵ We also examine the correlation between our local emotional exuberance with U.S.-level emotional exuberance, Baker and Wurgler (2006) investor sentiment, University of Michigan's Consumer Confidence Index, Loughran and McDonald (2011) and Henry (2008) positive/negative-based tone measures. We find our local emotional exuberance has low correlations with these U.S.-level measures (see Panel B of Table 3.A.3).

3.4.1 Return Predictability Regression Estimates

Table 3.3 presents our baseline return predictability regression estimates. Consistent with our main conjecture, we find that the coefficient of the state market emotion index is positive and significant. The other state-level business cycle predictors of Korniotis and Kumar (2013), such as state-level relative unemployment, have the expected sign and significance. These baseline estimates provide initial evidence in favor of our return predictability hypothesis and confirm that increasing levels of state-level emotional exuberance-driven utility lead to higher state portfolio returns in the next quarter even in the presence of well-known state-level business cycle predictors. Their U.S.-wide counterparts have weaker and mostly insignificant coefficient estimates across all specifications.

The coefficient estimate of the state market emotion index is economically significant. The coefficient in column (4) indicates that a one standard deviation increase in state market emotion index is associated with a $0.02 \times 0.114 \times 4 \times 100 = 0.912\%$ increase in annualized characteristic-adjusted state portfolio return. Mean annualized characteristic-adjusted returns range from 0.912% to 1.14% across all states (see Table 3.3). Therefore, the state market emotion index measures economically significant shifts in state portfolio returns.

U.S. state industry composition varies widely. Regression specification (5) in Table 3.3 examines whether industry heterogeneity across states matters for our local return predictability. When we define residual returns using industry benchmarks, we find the state market emotion index is still a significant predictor of state portfolio returns. This evidence indicates that, taking into account state-level business cycles, investor emotions reflected in local newspaper articles are capable of identifying return predictability even after considering industry heterogeneity.

In the final regression specification, we recursively estimate Eq. (2) to avoid look-ahead bias and to use information available until quarter t . The first recursive regression is estimated in 1995 because we use a 5-year period to start the recursive procedure.¹⁶ We collect all the estimates and present the average coefficient estimate for each of the return predictors including the percentage of times that an estimate is statistically significant. The estimates presented in column (6) of Table 3.3 are similar to our baseline estimates. The average of the state market

¹⁶ We also perform a 3-year recursive estimate and find qualitatively similar results.

emotion index coefficient estimates is 0.021 and is statistically significant in 80% of cases. The result indicates that the evidence of predictability is strong even when we estimate predictability regression recursively.

3.4.2 Geography-based Trading Strategies

In this section, we examine the economic significance of our local return predictability models by constructing geography-based trading strategies. We formulate different types of trading strategies using state portfolio rankings. We use a recursive model to obtain the state ranking by utilizing the information up to time t to avoid look-ahead bias. This alternative method of assessing economic significance allows us to use a variety of unconditional and conditional factor models to account for risk and time-varying portfolio exposure to various U.S.-wide systematic risk factors.

3.4.2.1 Construction of Trading Strategies

At the end of each quarter t , we estimate predictability regression Eq. (2) recursively using characteristic-adjusted return as the dependent variable. We use the estimated model in quarter t to predict the state portfolio return in quarter $t + 1$ and rank all U.S. states based on their predicted quarterly returns. To construct portfolios based on state rankings, we follow the method of Korniotis and Kumar (2013).

We construct four portfolios using predicted state ranking. The “Long” portfolio contains firms located in the four states (i.e., $N_S = 4$, where N_S is the number of states in the extreme portfolios) with the highest predicted returns next quarter.¹⁷ The “Short” portfolio contains firms located in the four states with the lowest predicted returns next quarter. Stocks in the remaining states are in the “Others” portfolio. Finally, we construct the “Long-Short” portfolio that represents the difference between the returns of the Long and Short portfolios. We rebalance portfolios quarterly as state-level predictors are only available at a quarterly frequency. For robustness purposes, we check the alpha performance of the Long-Short portfolio by using a different number of states in the Long and Short portfolios.

¹⁷ All our results remain qualitatively similar when we use three extreme states in our Long and Short portfolios based on predicted returns next quarter.

We compute value-weighted portfolio returns for each of the four portfolios. For robustness, we also examine the equal-weighted average (not tabulated) of state portfolio returns. In some of our tests, we follow Korniotis and Kumar (2013) and use individual stock returns instead of state indices to measure the performance of geography-based portfolios. Weights, in this case, are the market capitalization of individual firms in the previous month instead of aggregate state-level market capitalization.

3.4.2.2 Graphical Evidence of Trading Strategy Performance

We assess the performance of our trading strategies using a variety of tests. We present graphical evidence of the superior performance of our geography-based trading strategy. We rank states using the recursive predictability model defined in Table 3.3, column (4), and include four states in the extreme “Long” and “Short” portfolios. Figure 3.1 shows the raw (Panel A) and characteristic-adjusted (Panel B) performance time-series for the Long-Short portfolio. The light line indicates the monthly performance measure, and the dark line indicates the 12-month backward moving average. The estimation period is from July 1995 to December 2018. From the graph, it is evident that the geography-based trading strategy performs well over the sample period as 165 and 175 months out of 282 months generates positive returns respectively across the raw and characteristic-adjusted return models. Both raw and characteristic-adjusted performance measures yield qualitatively similar results.

Next, we assess the economic significance of the performance of the geography-based trading strategy. In Figure 3.2, we plot the performance of Long and Short portfolios relative to the market return. Our trading strategy outperforms the market throughout the sample period. One dollar invested in the market grows to about 7 dollars during the period of 1995 to 2018 whereas a dollar invested in the Long strategy during the same period grows about 30 dollars. During the dot.com bubble and financial crisis, all portfolios and market return experience a decline. Figures 3.1 and 3.2, taken together indicate that an emotional exuberance-driven geography-based trading strategy outperforms the market by a good margin over the 23-year evaluation period.

3.4.2.3 Baseline Estimates of Performance of Trading Strategies

We estimate the mean monthly returns of our geography-based trading strategies for the years 1995 to 2018. Table 3.4 Panel A, reports average raw, market-adjusted, and characteristic-adjusted returns. We also report performance estimates for the “Others” portfolio. Figure 3.3

provides performance estimates for the 1995 to 2007 and 2007 to 2018 subperiods; risk adjusted average returns are similar across the three return-adjustment models and for the two subperiods.

We find that our geography-based trading strategy is robust and economically significant. Long-Short portfolio performance is statistically and economically significant for the full sample and subperiods irrespective of the choice of performance measure. Specifically, the evidence in Table 3.4, Panel A, indicates that, during the evaluation period, the Long portfolio earns a monthly return of 1.182% (t -statistic = 3.77), whereas the Short portfolio earns only 0.372% (t -statistic = 1.09), and the Others portfolio has an average return of 0.595% per month. Average return monotonically decreases from Long to Short geography-based portfolios. The Long-Short portfolio generates a statistically significant monthly average return of 0.81% (t -statistic = 3.53) that translates into an annual performance differential of about 9.72%. The characteristic-adjusted performance differential is about 5.23% (t -statistic = 3.14) on an annualized basis, and the difference is also economically significant.¹⁸

Next, we examine the performance of our emotional exuberance-driven geography-based trading strategies using various unconditional factor models. Results are similar. To measure the risk-adjusted performance of geography-based trading strategies our factor models contain a combination of the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the operating profitability factor (RMW), the investment factor (CMA), the short-term reversal factor (STR), the long-term reversal factor (LTR), and the liquidity (LIQ) factor. Results are reported in Panel B of Table 3.4.

Performance of the emotional exuberance-driven geography-based trading strategy remains economically significant across different factor models. For example, the monthly 3-factor alpha (t -statistic) estimates for Long, Short, and Long-Short portfolios are 0.519 (4.02), -0.302 (-2.01), and 0.821 (4.06), respectively. When we control for 9-factors, the Long-Short alpha estimate translates into an annual risk-adjusted performance of about 9.17%.

¹⁸ When we use the extreme three states in the Long and Short portfolios, the Long-Short portfolio using raw returns yields 0.605% with a t -statistic of 2.36 and 0.373% with a t -statistic of 2.22 on a characteristic-adjusted basis.

3.4.2.4 Conditional Factor Model Performance Estimates

In this subsection, to take into account the time-varying exposures of our emotional exuberance-driven geography-based portfolios to U.S. systematic risks we employ three conditional factor models. Specifically, we obtain alpha estimates for Long, Short, and Long-Short portfolios after allowing for time-variation in portfolio exposures to U.S. systematic risk factors. The first conditional factor model is from Lettau and Ludvigson (2001a, 2001b), and includes 8 systematic factors: the three Fama-French factors (i.e., RMRF, SMB, and HML), the momentum factor (UMD), and the interactions of these factors with the mean-free lagged value of the U.S. *cay* residual. The *cay* residual is defined as the difference between current consumption (c) and its long-term value based on assets (a) and income (y). Baker and Wurgler (2006) use a similar interaction-based method to account for time variation in exposures to systematic risk factors. The second conditional model also contains eight factors, namely, RMRF, SMB, HML, UMD, and the interactions of these factors with a recession indicator, REC, that takes the value of one for quarters identified as recession quarters by the NBER. The third conditional model has 12 factors, which include the four typical risk factors (i.e., RMRF, SMB, HML, and UMD) and their interactions with the U.S. *cay* residual as well as the REC dummy variable.

We report the conditional alpha estimates and factor exposures in Table 3.5. Results indicate that the alpha estimates remain economically significant when we use different conditional factor models to account for portfolio risk. For example, Long-Short portfolio monthly alpha estimates are 0.649 (t -statistic 3.35) when we use the Lettau and Ludvigson (2001a) *cay* residual-based conditional model, 0.749 (t -statistic 3.56) with the conditional model with NBER recession interactions, and 0.712 (t -statistic 3.30) with the extended 12-factor conditional model, respectively. Both alphas and their statistical significance of the Long, Short, and Long-Short portfolios are lower in the case of conditional factor models. However, although abnormal performance estimates weaken, the Long-Short portfolio alpha estimates remain statistically significant across all conditional factor models.

3.4.3 Strength of the Local Mispricing

In this section, we explore the performance of our emotional exuberance-driven geography-based trading strategies. So far, our results indicate that our trading strategies offer abnormal performance when we use various unconditional and conditional factor models. One

explanation for this is that it reflects mispricing generated by variations in local investors emotional exuberance-driven utility. However, once such mispricing is identified it will eventually be arbitrated away by nonlocal investors. To test this mispricing and correction conjecture, we first test the performance of our strategies over the longer term. We then examine trading strategy performance for subsamples in which the potential impact of local clienteles vary.

3.4.3.1 Long Horizon Trading Strategy Performance

We examine the ability of our emotional exuberance-driven geography-based trading strategy to exploit locally-generated mispricing. If such a trading strategy is able to exploit such mispricing, then as the prediction horizon h increases, Long-Short portfolio performance will gradually deteriorate as nonlocal investors become more active in arbitrating away any local mispricing. Speed of adjustment indicates the effectiveness of arbitrage forces in correcting the mispricing our emotional exuberance-driven geography-based trading strategy identifies.

Specifically, we construct a series of trading strategies based on state rankings from an h -quarter-ahead recursive predictive regression to avoid look-ahead bias of the following form:

$$Y_{j,t+h-1} = \alpha_j + X_{j,t-1}^{MEI} \delta_1 + X_{j,t-2} \delta_2 + X_{USA,t-2} \delta_3 + \log(1 + D/P)_{j,t-1} \delta_4 + \varepsilon_{j,t+h-1} \quad (4)$$

The dependent variable is the h -quarter-ahead characteristic-adjusted return of state portfolio j . For $h > 1$, the estimation period decreases by $h - 1$ quarters. For each h , we form Long, Short, and Long-Short portfolios based on predictive state portfolio return. We evaluate the performance of these strategies using both 9-factor unconditional and 12-factor conditional models. The 9-factor unconditional model includes the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the operating profitability factor (RMW), the investment factor (CMA), two reversal factors (short-term reversal (STR), long-term reversal (LTR), and the liquidity factor (LIQ). Our 12-factor conditional model includes RMRF, SMB, HML, and UMD factors, and the interactions between these four factors and the *cay* residual of Lettau and Ludvigson (2001a, 2001b) and the NBER recession indicator. The NBER recession indicator is set to one for quarters in which the U.S. economy experienced a contraction.

Table 3.6 presents the trading strategy performance in the longer run. We find that as h increases emotional exuberance-driven geography-based Long-Short portfolio alpha estimates

decline. In Panel A, for example, as the prediction horizon h increases from 1 to 8 quarters, the alpha estimates (t -statistic) for the Long-Short portfolios decrease from 0.764 (4.10) to 0.331 (1.40). In Panel B, the conditional factor model alpha (t -statistic) reduces from 0.712 (3.30) to 0.226 (1.00). This declining pattern indicates that local mispricing is corrected in about six-months. Beyond 2 quarters the alpha estimates become small and statistically insignificant for both models.

3.4.3.2 Firm Visibility and Trading Strategy Performance

To further investigate the local mispricing induced by local investor clienteles' emotional exuberance-driven utility, we explore subsamples of stocks that local investors impact heavily. To capture the strength of the impact of local investor clientele, we construct a firm visibility measure similar to Hong, Kubik, and Stein (2008) and Korniotis and Kumar (2013). This is the residual of a regression of the log number of shareholders on the log of firm sales. Specifically, we define firms in the bottom (top) tercile based on the visibility index as low (high) visibility firms, and find that emotional exuberance-driven geography-based trading strategy performance varies with the level of firm visibility.

In Panel A of Table 3.7, we find that mispricing is stronger for the low visibility subsample as less visible firms are likely to have stronger local clienteles (see, for example, Hong, Kubik, and Stein, 2008; Korniotis and Kumar, 2013). The 12-factor conditional alpha estimate for the Long-Short portfolio in the low visibility subsample is 0.757 (t -statistic = 2.56) compared to an alpha of 0.432 (t -statistic = 1.74) for the high visibility subsample. This provides evidence that returns of less visible local firms are more sensitive to changes in local investor emotional exuberance. If, indeed, less visible firms have stronger investor clienteles, then this evidence supports our conjecture that a significant part of the trading strategy performance we identify can be attributed to local investor emotional exuberance.

We also focus on the correction pattern of local mispricing. We conjecture that initially nonlocal investors might not be aware of the local mispricing and as they become more informed arbitrage forces will quickly attenuate this mispricing. However, local mispricing is likely to be strongest for firms in the low visibility subsample before showing signs of correction. Consistent with our prediction, in Panel B of Table 3.7, we find that in the low visibility subsample mispricing continues up to six-months into the future before becoming statistically insignificant. The alpha estimate reduces from 0.757 (t -statistic = 2.56) to 0.373 (t -

statistic = 0.99) after 8 quarters. The high visibility subsample remains devoid of any mispricing and correction.

Taken together, we find local investor emotional exuberance-driven utility creates mispricing, and this is more pronounced for firms with stronger local clienteles. Once nonlocal investors identify local mispricing abnormal performance becomes insignificant in about six-months. This evidence supports our conjecture that greater local emotional exuberance leads to higher abnormal state portfolio return.

3.4.4 Drivers of Local Mispricing

To tease out the drivers of local mispricing, we provide average state characteristics and demographics across our four portfolios – Long, Others, Short, and Long-Short – in Table 3.8. Our main state variable, market emotion index, monotonically reduces from Long to Short portfolios. Average emotional exuberance-driven utility for the Long-Short portfolio is 0.044 and statistically significant (t -statistic = 3.04). This finding is consistent with our main conjecture that high local emotional exuberance-driven utility predicts higher local stock returns in the future, and leads to consequent mispricing. Other state-level predictors such as state income growth, housing collateral ratio, and log of dividend price ratio in the Long-Short portfolio are also statistically significant. This result showcases that our state-level market emotion index measure complements other state-level return predictors in identifying local mispricing.

Ekman et al. (1987) and Matsumoto (1993) find that emotions vary on the basis of culture, ethnicity, and the psychological makeup of individuals. We examine demographic differences between states assigned to our Long and Short portfolios. States in the Long portfolio have a higher percentage of educated residents compared to the Short portfolio with educational differential of the order of 2.6% (t -statistic = 3.19). Educated residents are expected to follow newspapers more and take into account what is written more in their financial decision-making. Goetzmann et al. (2016) point out how the media mediates individuals and institutional investors' crash beliefs. There are also 10.8% fewer non-white residents (t -statistic = -8.89) in Long compared with Short portfolio states. In addition, populated states dominate less-populated states and have a greater impact on trading activities. A larger state population is likely to translate into a greater exposure to newspapers potentially further fuelling emotional exuberance in driving abnormal stock returns. In addition, Goetzmann et al. (2016) find that

influenced by newspaper stories high income individuals exaggeratedly anticipate a stock market crash. We find our Long portfolio includes high income and less poverty-stricken states. High income translates into greater stock market participation, and more awareness about the market events covered by local newspapers. Consequently, a stronger emotional engagement with the stock market reinforces the emotional relationships local investors have with their local stocks leading to abnormal returns.

3.4.5 Is Emotional Exuberance Capturing Something Else?

In this section, we explore whether the local predictability mechanism we identify is due to investors' emotional exuberance, or is a repackaging of something else such as narrative tone, sentiment, local bias, local optimism, and local economic activity-based forecasts. Specifically, we examine our third hypothesis that integral emotional exuberance is distinct from incidental feelings. We examine these issues and test the incremental predictability of our emotional exuberance measure proxied by the local market emotion index in the following subsections.¹⁹

3.4.5.1 Is Emotional Exuberance Capturing Tone?

In our first set of tests, we examine whether emotional exuberance is measuring media-generated tone. Extant literature provides evidence of the relationship between tone derived from media and stock returns (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Hillert et al., 2014). Specifically, we control for two sets of tone measures. The first tone measure is based on Loughran and McDonald's (2011) positive and negative word lists. The second positive-negative word list is from Henry (2008).²⁰

Table 3.9 presents the results controlling for these two prominent finance-specific tone measures. In column (1), the coefficient of our state market emotion index remains economically significant consistent with our main conjecture that local emotional exuberance predicts local stock returns. In the presence of positive-negative tone, the state market emotion index still predicts next quarter state portfolio returns. In fact, the state market emotion index

¹⁹ We use state and year fixed effects in our predictive regressions though our results remain broadly consistent when we include region and year fixed effects.

²⁰ We construct two tone measures by analyzing the same media reports we use to derive our market emotion index as follows: $Tone_{j,t} = \frac{Positive_{j,t} - Negative_{j,t}}{Positive_{j,t} + Negative_{j,t}}$. We apply the positive and negative word lists of Loughran and McDonald (2011) and Henry (2008) to count positive and negative words.

and state relative unemployment together subsume the predictability power of the tone measures. Therefore, it is reasonable to assert that the emotional exuberance measure is teasing out something distinct from narrative tone.

3.4.5.2 Is Emotional Exuberance Capturing Sentiment?

Next, we examine whether sentiment, either investor or public, subsumes our emotional exuberance measure. The sentiment measures we control for are the Baker and Wurgler (2006) investor sentiment index and University of Michigan's Consumer Confidence Index. Our state market emotion index correlates at 0.062 and -0.020 with these sentiment measures respectively, providing initial evidence of the distinctiveness of our measure.

Table 3.9 column (2) presents the results when we include sentiment measures in our predictability regression. Our emotional exuberance measure proxied by the local market emotion index remains positive and significant. Thus, we can conclude that our emotional exuberance measure has incremental predictability to sentiment.

3.4.5.3 Is Emotional Exuberance Capturing Local Optimism?

Chhaocharia et al. (2019) show that mood affects the economic expectations of small business managers that captures local optimism. They use data from the Small Business Economic Trends (SBET) survey to measure the optimism and expectations of small business managers. The National Federation of Independent Business (NFIB) collects information for its survey by randomly selecting respondents from approximately 350,000 members. The NFIB regularly publishes small business optimism index on a regional basis, and we use these indices to proxy for local optimism level.²¹

We conjecture that our emotional exuberance measure can predict local future stock returns, but are we only picking up local business optimism? Small business managers enjoy more autonomy than corporate managers, so they are more impacted by incidental emotions such as mood (Chhaocharia et al., 2019). Thus, exploring predictability controlling for local optimism serves a twin purpose – measuring directly the effects of local optimism, and indirectly the impact of mood. Table 3.9 column (3) includes local small business optimism, and we still find that our integral emotion-driven exuberance has significant predictive ability

²¹ The small business optimism index is available at National Federation of Independent Business (NFIB) website.

at local level. Thus, we can safely eliminate concerns relating to the local emotional exuberance capturing local optimism or incidental mood.

3.4.5.4 Is Emotional Exuberance Capturing Local Economic Activity Forecast?

Local economic activity plays a significant role in the performance of local firms. Smajlbegovic (2019) shows that regional macroeconomic information positively predicts future stock returns as investors value news about future firm cash flows. We hypothesize that along with the utility of wealth investors also want to maximize their emotional or psychological utility. We speculate such emotional utility should have incremental predictability in the presence of local cash flow-based predictability. We follow Smajlbegovic (2019) and use the state-level economic activity forecast measured by the State Leading Index (SLI) of Crone and Clayton-Matthews (2005).²²

In column (4) of Table 3.9, we control for state-level leading indices. We find significant evidence in favor of our conjecture that local emotional exuberance has incremental ability in predicting local future stock returns. The results show that investors value and want to maximize their emotional utility as explained by Caplin and Leahy's (2001) theory of psychological expected utility.

3.4.5.5 Is Emotional Exuberance Capturing Local Bias?

The extant literature on home bias shows that investors prefer to hold domestic compared to foreign stocks (e.g., French and Poterba, 1991) and local compared to non-local stocks (e.g., Coval and Moskowitz, 1999). Hong, Kubik, and Stein (2008) find investors exhibit local stock bias preferring to invest in local stocks, and this bias affects local stock prices through an 'only game in town' effect.²³ As such we need to demonstrate local emotional exuberance is distinct from, and is not simply a repackaging of, local bias. To eliminate this possibility, we specifically control for local bias in our predictive regressions. In line with Hong, Kubik, and Stein (2008) we define local bias (RATIO) as the total of book value of equity of all the firms in a region in a quarter to the total of aggregate household income in that region in that quarter.

²² State Leading Index (SLI) data is available at Federal Reserve Bank of St. Louis. <https://fred.stlouisfed.org/searchresults?st=State+leading+index>.

²³ In the 'only game in town' effect, firms in regions with fewer firms have to face less competition in attracting investors and this drives their price up.

Table 3.9 column (5) reports the results of our predictive regression. We find that in the presence of local bias investors' emotional exuberance still predicts future stock returns. In fact, investor emotional exuberance is clearly distinct from their preference for local stocks.

Table 3.9, columns (6) and (7) includes all tone, sentiment, local optimism, local economic forecast, and local bias measures and finds evidence of incremental predictability of our emotional exuberance over and above these measures. Taken together, we provide comprehensive evidence in favor of our key conjecture that local investors' emotional exuberance predicts future local stock returns, and this predictability mechanism is unique and economically meaningful.

3.4.6 Robustness of Predictive Regression Estimates

We also perform several robustness tests of our baseline predictability regression. We first test whether the predictability we observe is driven by any particular state, region or overall market emotion, or second, any large firms dominating the state portfolios. Third, we test the impact of different variations of our market emotion index on our geography-based trading strategy. We also test our prediction models excluding different state- and U.S.-level predictors. Further, we test the significance of the alpha estimate across different firm subsamples.

3.4.6.1 Dominant States or Regions?

We examine whether our main results are driven by a few large states or certain geographic regions. We re-estimate Eq. (2) panel predictive regressions after excluding two large states (California and New York), and each of the four U.S. Census regions separately. Results in Table 3.10, rows (2) to (6), are consistent with our main results. Further, in test (9), we exclude states – Arkansas for Walmart and Washington for Amazon and Microsoft – with dominating firms. Still, results show evidence of strong return predictability. Overall, the evidence from these tests supports our main conjecture that local emotional exuberance predicts state portfolio returns, and the results are not region or state specific.

3.4.6.2 Impact of Oil Prices

Changes in oil prices can affect the local economy that in turn could impact local stock returns. In tests (7) and (8), we exclude states that are major oil producers and consumers. Oil-producing states are California, Texas, and Louisiana that produced more than 500 barrels of

oil per day in 2007. Oil-consuming states are fifteen east coast states (see Chhaochharia et al., 2020), which consume more oil due to the usual cold temperatures. Results indicate oil prices do not affect the predictability of emotional exuberance for state portfolio returns.

3.4.6.3 Alternative Measures of the Market Emotion Index

It is arguable that the predictability we find may be influenced by the construction of our market emotion index measure. With a different definition of the state market emotion index, we may find no predictability. To accommodate this line of argument, we construct two variations of our market emotion index. First, we use the ratio of difference between excitement and anxiety word counts in a quarter to total words across all news articles in that quarter. We term this Net MEI and it is derived as follows:

$$Net\ MEI_{j,t} = \frac{Excitement_{j,t} - Anxiety_{j,t}}{Total\ Words_{j,t}} \quad (5)$$

Second, we work with all the seven emotion categories proposed by Taffler et al. (2021) and divide all the emotions into two broad extreme dimensions. The first dimension ‘excitement’ comprises of excitement and mania, and the second dimension ‘anxiety’ includes anxiety, blame, denial, guilt, and panic. We term this measure Total MEI and construct it as follows:

$$Total\ MEI_{j,t} = \frac{(Excitement_{j,t} + Mania_{j,t}) - (Anxiety_{j,t} + Blame_{j,t} + Denial_{j,t} + Guilt_{j,t} + Panic_{j,t})}{Total\ Words_{j,t}} \quad (6)$$

We re-estimate our predictability regression using these two alternative measures and present the coefficients in rows (10) and (11) of Table 3.10. In both cases, we find the coefficient is statistically significant. Thus, the way in which we measure our market emotion index does not pose any significant concern.

3.4.6.4 Impact of Unobserved Region Effects

Since we use the regional market emotion index as a proxy for state-level market emotion index to capture emotional exuberance, it is arguable that we are capturing some unobserved regional effects. To examine this line reasoning, in the second last set of predictive regression tests in row (12), we use region and year fixed effects to account for unobserved regional and time-dependent variables. Results remain significant and very similar to our baseline estimates.

3.4.6.5 Impact of Overall Market Emotion

In this subsection, we examine whether local emotional exuberance-based predictability goes beyond the overall market emotional exuberance. It is arguable that the evidence of predictability we report is reflecting market-wide emotional exuberance. To capture incremental local predictability, we use the market emotion index of chapter 2.

We report the results of our predictability regressions after controlling for the market emotion index in Appendix Table 3.A.4. We find that local emotional exuberance has positive and significant coefficients across different specifications. These results alleviate the concern that overall market emotions drive our predictability and show that local emotional exuberance has incremental predictability even in the presence of market-wide emotional exuberance.²⁴

Overall, the results from these different specifications support our predictability conjecture and indicate that the strong relationship between local emotional exuberance and state portfolio returns is unlikely to reflect unobserved state-level heterogeneity. Taken together, the results from our predictability regressions indicate that investors feel excited or anxious about the stock market as reflected in local newspapers articles, and trade in local stocks, which consequently leads to predictable patterns in stock returns.

3.4.7 Robustness of Trading Strategy Performance Estimates

For robustness purposes of performance estimates, we perform additional tests on our emotional exuberance-driven geography-based trading strategy. In particular, we examine trading strategies using alternative prediction models.

3.4.7.1 Alternative Prediction Models

Panel A of Table 3.11 presents the results of tests of alternative prediction models. In column (1), we use a standardized version of the state market emotion index with mean zero, and standard deviation of one. We find that the alpha remains economically and statistically significant. In columns (2) and (3), we use alternative variations of our market emotion index i.e., Net MEI and Total MEI, and still find positive and significant alphas. This evidence shows

²⁴ We also run the same predictive regression controlling for two market wide tone measures, Loughran and McDonald (2011) and Henry (2008) positive/negative tone, along with overall market emotion index. We find qualitatively similar results (unreported) that local emotional exuberance can still predict state portfolio returns next quarter.

that our prediction model estimates do not depend on the way we measure our emotion index. We also estimate the return prediction model using a qualitative model where we include the standardized state market emotion index together with Korniotis and Kumar's (2013) state economic activity index. To compute the latter index, we add the standardized values of state income growth and state hy , subtract the value of relative state unemployment, and divide the result by three. As reported in column (4), we still find positive and statistically significant alpha.

Next, in column (1) of Panel B, we exclude all the state-level predictors of Korniotis and Kumar (2013) and estimate the return prediction model. Again, this prediction model yields significant alpha estimates. As such our results are not driven by state-level macroeconomic predictors, and state-level emotional exuberance can reliably rank U.S. state portfolios to generate economically significant alpha estimates. In the next set of tests, in column (2), we exclude the U.S.-level predictors. We find that the performance of the Long-Short portfolio is still significant. In columns (3) and (4) we include tone alone, and tone and sentiment measures together in our return prediction model, and find that our emotional exuberance-driven geography-based trading strategy still generates significant abnormal returns.

We also examine whether the performance of the Long-Short portfolio varies with the number of states (N_S) in the extreme portfolios. If N_S is high, the estimation risk should be low but the distinction between extreme portfolios should weaken. If N_S is low, the estimation risk should be high, but the performance differentials should be reflected more accurately. Thus, we face a risk-accuracy trade-off (e.g., Kandel and Stambaugh, 1996; Barberis, 2000; Korniotis and Kumar, 2013). Figure 3.4 reports performance estimates for the Long-Short portfolio for different values of N_S . As expected, the Long-Short performance differential declines as N_S increases. However, we find that the Long-Short performance differential is statistically significant even for larger values of N_S . This evidence indicates that our results are not sensitive to the choice of $N_S = 4$ in our main empirical analysis. The unconditional 5-factor model alpha mostly exceeds the conditional 15-factor model alpha.

3.4.7.2 Firm Characteristics and Performance of Trading Strategies

To examine whether the evidence of return predictability and the performance of our trading strategies are stronger among certain types of stocks, we examine trading strategy performance estimates for subsamples with different stock characteristics. The main objective of this

analysis is to determine whether the performance of our geography-based trading strategies is realizable or whether the evidence of predictability is merely concentrated among subsets of stocks that are difficult to trade. In these tests, we identify all firms located in states that are in a geography-based portfolio and then obtain their value-weighted return to measure the performance of the portfolio. Portfolio weights are based on the market capitalization of firms at the end of the previous month.

Trading strategy performance estimates for stock attribute-based subsamples are reported in Panel C of Table 3.11. In the first subsample presented in column (1), we obtain performance estimates after excluding all financial firms. We find that the monthly alpha estimate from the conditional factor model decreases from 0.712% in our baseline model to 0.648% but still remains highly significant. Next, following Korniotis and Kumar (2013) we exclude firms known to have higher local ownership, namely growth stocks in column (2), low-priced stocks in column (3), and stocks with lower market capitalization in column (4). We find that trading strategy performance remains economically and statistically significant.

Taken together, evidence from alternative prediction models, different market emotion index constructions, and firm attribute-based subsamples indicates that the relation between local emotional exuberance and local stock returns is robust and economically significant. Our geography-based trading strategies generate high and statistically significant risk-adjusted returns for different stock subsamples.

3.5 Summary and Conclusions

Causal observation suggests investor emotions influence their decision-making. In this paper, we construct a local market emotion index to measure local investor emotional exuberance and test whether this can explain local return predictability. Specifically, we propose the emotional utility investors experience from the stock market varies with their locality and reinforces their relationships with geographically-proximate stocks. We define our local market emotion index, representing the notion of emotional exuberance-based utility, as the ratio of the difference between excitement and anxiety words to the total of excitement and anxiety word counts in local newspaper articles about the stock market.

Our key conjecture is that local stock returns vary with local emotional exuberance in a predictable manner. Emotions vary across ethnicity and psychological culture because of

factors such as education, geography, climate, and politics etc. (e.g., Ekman et al., 1987; Matsumoto, 1993). Thus, investors in different geographical regions of the U.S. are likely to have different emotional relationships with the stock market which, we posit, helps predict local stock returns. We measure the emotional relationship of investors with respect to the stock market as proxied by the state-level emotional exuberance. Specifically, exciting news about the stock market increases investors propensity to invest in local stocks with an expectation that prices will rise generating a positive abnormal return. On the other hand, anxious investors across different states do the opposite leading to lower abnormal returns.

Consistent with this conjecture, we find U.S. state portfolios earn high future returns when emotional utility is high. Exploiting this predictability during the 1995 to 2018 period, our emotional exuberance-driven geography-based trading strategies earn an abnormal annualized risk-adjusted return of 9.17%. Local mispricing is stronger for firms with low visibility and takes about six-months to be arbitrated away by nonlocal investors. Our local emotional exuberance-driven predictability is different from local narrative tone, sentiment, local optimism, local economic forecast, and local bias. This predictability also remains significant controlling for large states (such as California and New York), oil-producing states (such as California, Texas, and Louisiana), and dominant firm states (such as Arkansas for Walmart and Washington for Amazon and Microsoft).

Our findings make an important contribution to several strands of the literature. Our empirical findings indicate that the stock return generating process contains an additional predictable local component in the form of local emotional exuberance-driven utility. Thus, existing asset pricing models could be improved by including a geography-based emotional factor. Further, our results suggest that investors' differential emotional relationships with local stocks at the state-level generates frictions that segment the stock market geographically. Our findings complement evidence of market segmentation in other related settings (e.g., Becker, Ivkovich, and Weisbenner, 2011; Korniotis and Kumar, 2013; Chhaochharia et al., 2019, 2020). Also, emotion-driven geographical segmentation can help firms alter their cost of capital by relocating headquarters within the United States.

In addition, the paper contributes to the local return predictability literature. We establish a strong emotion-driven geographical dimension to return predictability and show that state portfolio returns can be predicted using state-level emotional exuberance. The evidence indicates that investors' understanding, and perception of stock market-related news

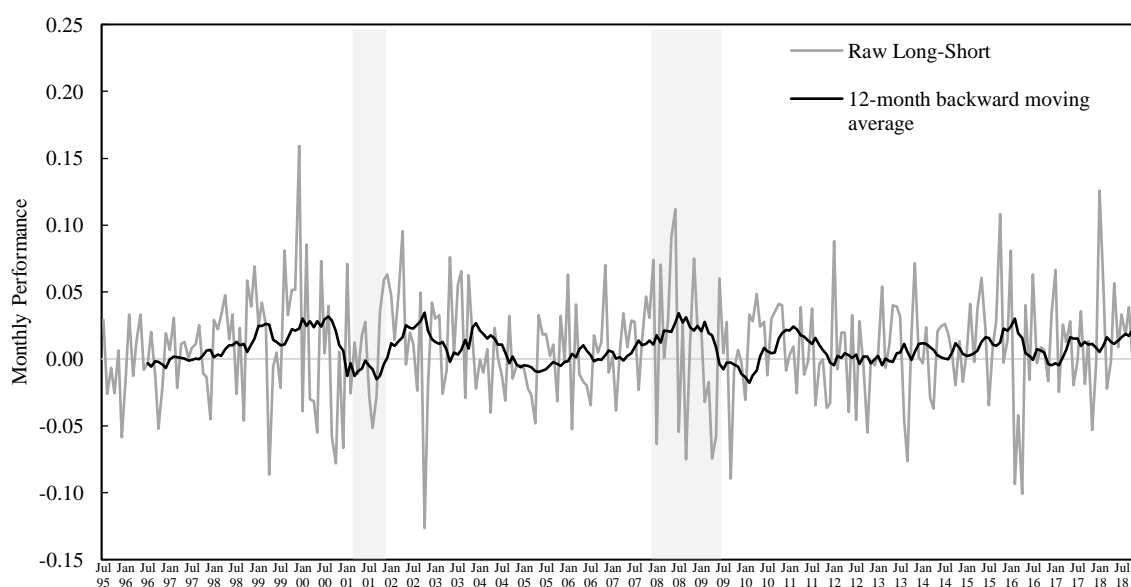
varies across states creating the opportunity to predict stock returns. Our paper also adds to the recent investor integral emotion-based return predictability (e.g., Bin Hasan et al., 2021) emphasizing a local predictability mechanism.

Overall, our results show that it is important to recognize the incremental role of integral emotions, such as excitement and anxiety, in financial decision-making. However, despite our strong empirical results, we acknowledge the difficulty in measuring investor emotions directly meaning we have to adopt an indirect approach to capture them. Thus, our results need to be cautiously interpreted. Nonetheless, our strong findings and the results of a wide range of robustness tests are consistent with our local market emotion index measure having empirical validity.

Figure 3. 1: Monthly Trading Strategy Performance Time Series

The figure shows the raw (Panel A) and characteristic-adjusted (Panel B) performance time series for our geography-based Long-Short trading strategy described in Table 3.4. The light line indicates the monthly performance measure, and the dark line shows the 12-month backward moving average of this measure for each month between July 1995 and December 2018. We include four states in the extreme portfolios, which are chosen based on the predictability model presented in Table 3.3 column (4) and the only difference is using a recursive estimate. The shaded regions are recession periods based on NBER recession indicators.

Panel A: Raw return



Panel B: Characteristic-adjusted return

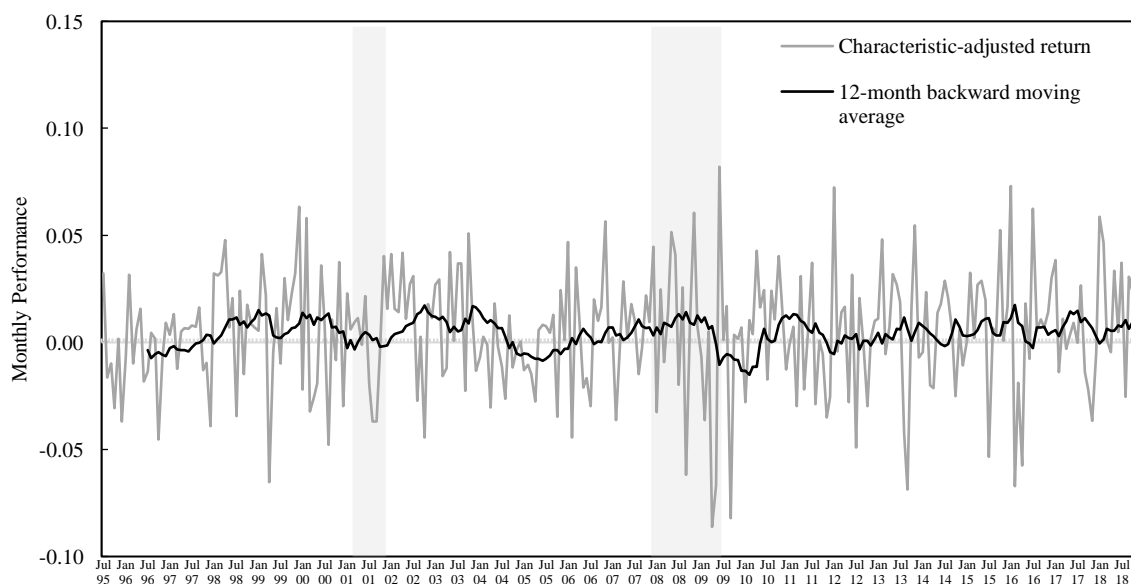


Figure 3. 2: Performance of Geography-based Long and Short Portfolios versus the Market

The figure shows the relative performance of Long and Short portfolios along with the performance of the aggregate stock market. The construction of the portfolios is described in the caption of Table 3.4, where the portfolios are formed using the baseline predictability model presented in Table 3.3 column (4). The shaded regions are recession periods based on NBER recession indicators. The estimation period is from July 1995 to December 2018.

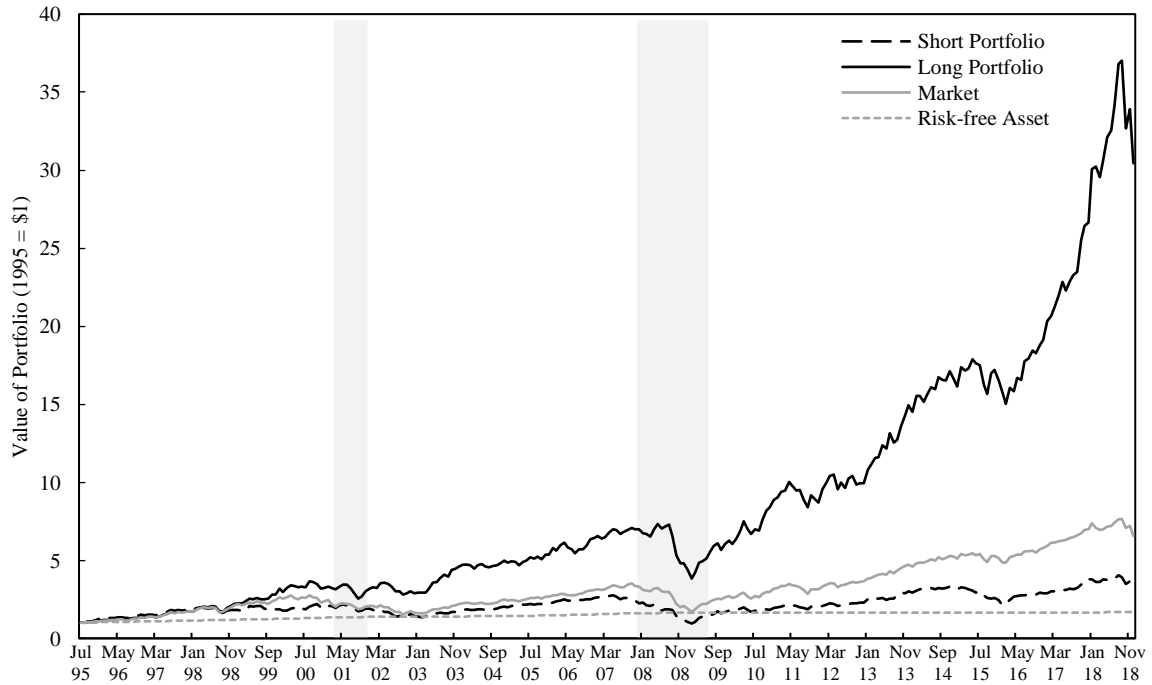


Figure 3. 3: Subsample Estimates

The figure shows the raw, characteristic, and industry-adjusted performance estimates of our baseline Long-Short trading strategy evaluated over different subperiods. The construction of the portfolios is described in the caption of Table 3.4 and the portfolios are formed using the baseline predictability model presented in Table 3.3 column (4). The evaluation period is from July 1995 to December 2018.

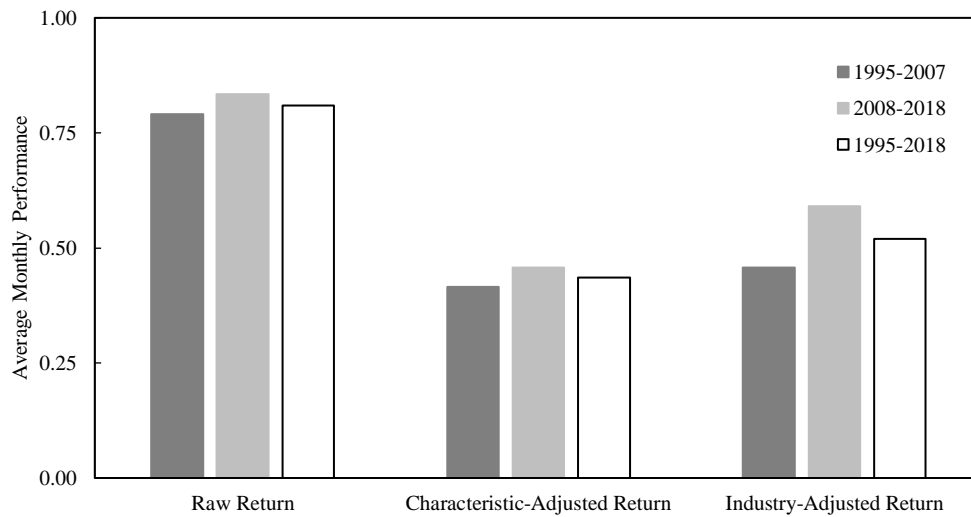


Figure 3. 4: Sensitivity to the Number of States in the Extreme Portfolios

The figure presents the alpha estimates for the Long-Short portfolio as the number of states in the extreme portfolios varies from 1 to 20. The construction of the portfolios is described in the caption of Table 3.4 and the portfolios are formed using the baseline predictability model presented in Table 3.3 column (4). The alphas are computed using the 5-factor unconditional and 15-factor conditional models. The 5-factor model includes the Fama-French factors – market, size, value, operating profitability, and investment. The factors in the conditional model include the Fama-French 5-factors as well as the interaction of these factors with an NBER recession dummy and the U.S. *cay* residual. The evaluation period is from July 1995 to December 2018.

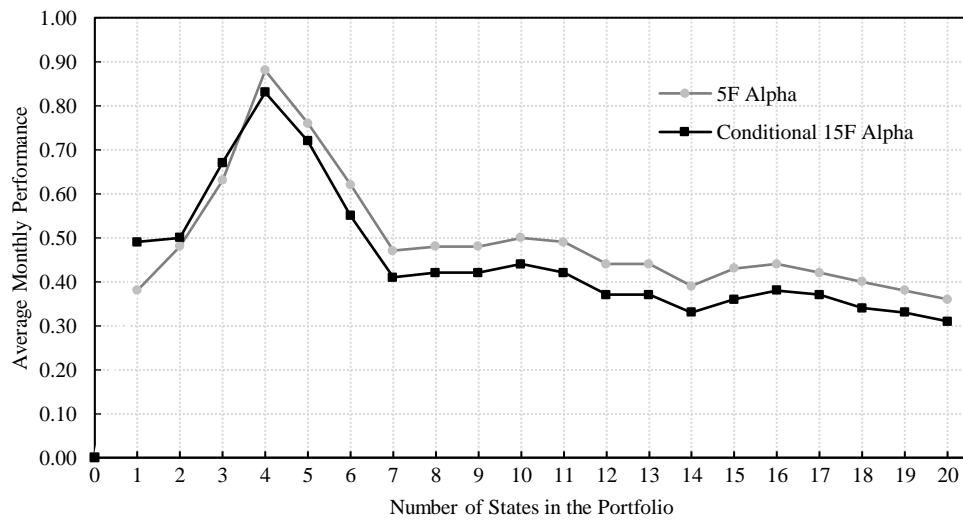


Table 3. 1: Sample Statistics

The table reports sample statistics for state portfolio returns, market emotion index, tones, state and U.S.-level return predictors, and state demographics. The sample period is from 1990 to 2018. In panel A, we report the summary statistics of state market emotion index, tones, state- and U.S.-level return predictors. State portfolios with fewer than 15 firms are excluded from the sample. The main return variable is the DGTW characteristic adjusted state portfolio return (R_{local}). The returns are divided by one plus the inflation rate collected from CRSP. State market emotion index which measures local emotional exuberance, and tones are generated using newspaper articles from 47 newspapers mentioned in Table 3.A.1 that covers four U.S. census regions. The state market emotion index is the ratio of the difference between excitement and anxiety word counts to the sum of excitement and anxiety word counts. The two-tone measures are the ratio of the difference between positive and negative word counts to the sum of positive and negative word counts. The state- and U.S.-level return predictors include labor income growth rates, relative unemployment rate, housing collateral ratio, the paper-bill spread, the term spread, default spread, the U.S. *cay* residual of Lettau and Ludvigson (2001a, 2001b), and state-level dividend-price ratio. The dividend is the sum of the past four quarterly dividends and price is the stock price at the end of the most recent quarter. The state housing collateral ratio is computed using the Lustig and van Nieuwerburgh (2005) method and following Kornoitis and Kumar (2013). The unemployment rates are from BLS. The relative unemployment rate is the ratio of the current unemployment rate to the moving average of the unemployment rates from the previous 16 quarters. Labor income is from BEA. U.S. *cay* and U.S. housing collateral ratio are downloaded from Sydney Ludvigson's and Stijn van Nieuwerburgh's web sites, respectively. The three spread data are from the Federal Reserve Bank of St. Louis. To compute the state economic activity index, we add the standardized values of state income growth and state *hy*, subtract the standardized value of relative unemployment, and divide this sum by three. In panel B, we report state demographics. All state demographics are from the U.S. Census. The annual census data are linearly interpolated to get quarterly observations. Education is the proportion of state residents over the age of 25 with a bachelor's degree or higher. The minority is the proportion of state residents who are non-white. Urban is the proportion of state residents living in urban areas. Poverty is the proportion of state residents who are poor according to the U.S. Census. The sample is from January 1990 to December 2018.

| Panel A: Summary statistics of state- and U.S.-level predictors | | | | |
|---|-------------------|--------|-----------|-----------------|
| Variable | Short Name | Mean | Std. Dev. | Autocorrelation |
| State Portfolio Return | R_{local} | 1.439 | 0.066 | 0.036 |
| State Market Emotion Index | State MEI | 0.182 | 0.114 | 0.314 |
| State Loughran-McDonald | State LM | -0.302 | 0.130 | 0.506 |
| State Henry | State HN | 0.197 | 0.145 | 0.494 |
| State Income Growth | State Inc Gr | 4.489 | 0.022 | 0.811 |
| State Relative Unemployment | State Rel Unemp | 0.997 | 0.266 | 0.965 |
| State Housing Collateral Ratio | State <i>hy</i> | -0.056 | 0.128 | 0.938 |
| U.S. Income Growth | US Inc Gr | 4.626 | 0.022 | 0.841 |
| U.S. Relative Unemployment | US Rel Unemp | 0.993 | 0.246 | 0.968 |
| U.S. Housing Collateral Ratio | US <i>hy</i> | -0.083 | 0.083 | 0.981 |
| Dividend-to-Price Ratio | $\log(1+D/P)$ | 0.019 | 0.010 | 0.942 |
| U.S. <i>cay</i> Residual | US <i>cay</i> | 0.003 | 0.016 | 0.896 |
| 30-day Commercial Paper – 30-day T-Bill | Paper-Bill Spread | 0.026 | 0.022 | 0.979 |
| Ten-Year – 1-Year Government Bond | Term Spread | 0.015 | 0.010 | 0.931 |
| Baa Corporate Bond – 1-Year Government Bond | Default Spread | 0.024 | 0.007 | 0.858 |
| State Economic Activity Index | State Econ Act | -0.019 | 0.660 | 0.922 |
| Panel B: State demographics | | | | |
| Demographic variable | Short Name | Mean | Median | Std. Dev. |
| Median Age | M_AGE | 36.188 | 36.200 | 2.568 |
| Education | EDU | 0.267 | 0.261 | 0.062 |
| Male-Female Ratio | MALE | 0.969 | 0.963 | 0.033 |
| Married | MARRIED | 0.523 | 0.525 | 0.052 |
| Minority | MINORITY | 0.186 | 0.156 | 0.137 |
| Urban Population | URBAN | 0.725 | 0.727 | 0.150 |
| Total Population (m) | TOTPOP | 5.712 | 3.899 | 6.413 |
| Median Income (m) | INCOME | 0.045 | 0.044 | 0.012 |
| Poverty | POVERTY | 0.133 | 0.127 | 0.034 |

Table 3. 2: Correlation Matrix

The table reports Spearman rank correlations between state portfolio returns, market emotion index, tones, state- and U.S.-level return predictors in panel A. The variable definitions are available in the caption of Table 3.1. The sample period is from January 1990 to December 2018.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| (1) DGTW R_{local} | 1 | 0.026 | -0.021 | -0.004 | 0.053 | 0.022 | -0.016 | 0.028 | 0.021 | -0.004 |
| (2) State MEI | | 1 | 0.437 | 0.439 | 0.071 | -0.035 | 0.082 | 0.089 | -0.048 | 0.144 |
| (3) State LM | | | 1 | 0.692 | 0.026 | -0.190 | 0.059 | 0.016 | -0.204 | 0.049 |
| (4) State HN | | | | 1 | -0.011 | -0.257 | 0.021 | 0.136 | -0.304 | 0.076 |
| (5) State Inc Gr | | | | | 1 | -0.225 | 0.136 | 0.605 | -0.095 | 0.052 |
| (6) State Rel Unemp | | | | | | 1 | 0.094 | -0.270 | 0.836 | -0.088 |
| (7) State hy | | | | | | | 1 | 0.028 | 0.078 | 0.569 |
| (8) US Inc Gr | | | | | | | | 1 | -0.282 | -0.114 |
| (9) US Rel Unemp | | | | | | | | | 1 | -0.134 |
| (10) US hy | | | | | | | | | | 1 |
| (11) $\log(I+D/P)$ | -0.053 | -0.068 | -0.052 | -0.129 | -0.103 | 0.111 | 0.011 | -0.067 | 0.108 | -0.033 |
| (12) US cay | 0.012 | 0.083 | 0.039 | -0.080 | 0.356 | 0.123 | 0.128 | 0.314 | 0.226 | -0.224 |
| (13) Paper-Bill Spread | 0.042 | 0.197 | 0.052 | 0.023 | 0.531 | -0.127 | 0.289 | 0.521 | -0.087 | 0.084 |
| (14) Term Spread | -0.002 | -0.047 | -0.008 | -0.162 | -0.387 | 0.545 | -0.132 | -0.608 | 0.591 | -0.079 |
| (15) Default Spread | 0.007 | -0.292 | -0.244 | -0.311 | -0.435 | 0.327 | -0.221 | -0.549 | 0.329 | -0.228 |
| (16) State Econ Act | 0.008 | 0.177 | 0.189 | 0.200 | 0.603 | -0.558 | 0.371 | 0.494 | -0.416 | 0.358 |

Table 3. 3: Baseline Panel Predictive Regression Estimates

The table reports the results from panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-1}^{MEI}\delta_1 + X_{j,t-2}\delta_2 + X_{USA,t-2}\delta_3 + \log(1 + D/P)_{j,t-1}\delta_4 + \varepsilon_{j,t}$. Specifically, we predict the quarterly state portfolio return in quarter t using lagged state-level market emotion index and macroeconomic variables measured in quarter $t - 1$ or $t - 2$. The dependent variable $Y_{j,t}$ is the difference between the state return and a benchmark return. In columns (1) to (4), the dependent variable is the characteristic-adjusted return computed using the Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) method. In column (5), the dependent variable is the industry-adjusted return computed using the 38 Fama and French (1997) industry categories. The row vectors $X_{j,t-1}^{MEI}$ contain the state market emotion index. The row vectors $X_{j,t-2}$ and $X_{USA,t-2}$ contain the state- and U.S.-level predictors, respectively. The predictability regressions are estimated using OLS. In columns (1) to (5), we report full-sample OLS estimates. In column (6) we report the recursive estimates. The t -statistics are reported in parentheses beneath the estimates use serial and cross-sectional correlation adjusted Driscoll and Kraay (1998) standard errors. The estimation period is from 1990 to 2018.

| Predictor | Benchmark for Computing Residual Return | | | | | |
|--|---|-------------------|-------------------|-------------------|-------------------|------------------|
| | DGTW (1) | DGTW (2) | DGTW (3) | DGTW (4) | Industry (5) | Recursive (6) |
| <i>Main Predictors</i> | | | | | | |
| State MEI | 0.025 (3.58) | 0.023 (2.93) | 0.025 (3.31) | 0.020 (2.35) | 0.007 (2.14) | 0.021 (80%) |
| <i>State-level Business Cycle Predictors</i> | | | | | | |
| State Inc Gr | | 0.028 (0.27) | 0.008 (0.08) | 0.013 (0.14) | -0.005 (-0.27) | 0.152 (64%) |
| State Rel Un | | 0.019 (3.45) | 0.013 (2.14) | 0.012 (1.96) | 0.005 (1.80) | 0.018 (67%) |
| State hy | | -0.007 (-0.93) | -0.004 (-0.50) | -0.006 (-0.68) | -0.006 (-1.57) | -0.010 (19%) |
| <i>Other Predictors</i> | | | | | | |
| $\log(1+D/P)$ | | | | 0.264 (1.94) | 0.090 (1.32) | -0.305 (77%) |
| US Inc Gr | | | 0.041 (0.23) | 0.045 (0.31) | -0.023 (-0.58) | 0.053 (21%) |
| US Rel Un | | | 0.031 (1.14) | 0.013 (0.39) | -0.006 (-0.56) | -0.010 (32%) |
| US hy | | | -0.089 (-1.44) | -0.182 (-2.21) | -0.008 (-0.27) | -0.016 (58%) |
| US cay | | | | -0.749 (-2.74) | 0.029 (0.22) | -0.468 (88%) |
| Paper-Bill Spd | | | | 0.407 (0.89) | 0.065 (0.37) | 0.187 (64%) |
| Term Spd | | | | 0.525 (1.01) | -0.155 (-0.90) | -0.266 (28%) |
| Default Spd | | | | -0.188 (-0.44) | 0.415 (2.93) | 0.616 (78%) |
| Adj. R^2 | 0.025 | 0.026 | 0.027 | 0.029 | 0.054 | 0.014 |
| N obs | 5028 | 5028 | 5028 | 5028 | 5028 | 5028 |

Table 3. 4: Performance of Trading Strategies: Baseline Estimates

The table reports the performance estimates of trading strategies defined using the return prediction model. We report the performance estimates of four portfolios: (i) the “Long” portfolio is the value-weighted portfolio of the state portfolios for the U.S. states predicted to have the highest four ($N_S = 4$) characteristic-adjusted returns in the next quarter; (ii) the “Short” portfolio is the value-weighted portfolio of the state portfolios for the U.S. states predicted to have the lowest four characteristic-adjusted returns in the next quarter; (iii) the “Long-Short” portfolio captures the difference in returns of the Long and Short portfolios; and (iv) the “Others” portfolio includes states that are neither in the Long nor in the Short portfolios. The recursive estimates from Table 3.3 column (4) are used to generate state rankings. State portfolios with fewer than 15 firms are excluded from the analysis. In Panel A, we report the raw, market-adjusted, and characteristic-adjusted performance estimates. The characteristic-adjusted return is computed using the Daniel et al. (1997, DGTW) method. In Panel B, we report the performance estimates using unconditional factor models. The factor models contain following factors: the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the operating profitability factor (RMW), the investment factor (CMA), two reversal factors (short-term reversal (STR), long-term reversal (LTR)), and the liquidity factor (LIQ). 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 July 1995 to December 2018.

| Panel A: Raw, market- and characteristic-adjusted performance | | | |
|---|-----------------|------------------------|--------------------------------|
| Portfolio | 1995 to 2018 | | |
| | Raw Return | Market-adjusted Return | Characteristic-adjusted Return |
| Long | 1.182 (3.77) | 0.589 (4.33) | 0.263 (2.71) |
| Others | 0.595 (2.24) | 0.001 (0.02) | -0.001 (-1.64) |
| Short | 0.372 (1.09) | -0.221 (-1.21) | -0.173 (-1.66) |
| Long-Short | 0.810 (3.53) | 0.810 (3.53) | 0.436 (3.14) |

Table 3. 4: Continued

| Panel B: Unconditional factor model estimates | | | | | | | | | | | | |
|---|------------------|-------------------|-------------------|------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|--------------------|
| Factor | Portfolio | | | | | | | | | | | |
| | Long (1) | Short (2) | Long-Short (3) | Long (4) | Short (5) | Long-Short (6) | Long (7) | Short (8) | Long-Short (9) | Long (10) | Short (11) | Long-Short (12) |
| Alpha | 0.519 (4.02) | -0.302 (-2.01) | 0.821 (4.06) | 0.494 (3.89) | -0.179 (-1.20) | 0.673 (3.51) | 0.534 (3.92) | -0.348 (-2.38) | 0.882 (4.50) | 0.532 (3.89) | -0.232 (-1.51) | 0.764 (4.10) |
| RMRF | 1.005 (25.36) | 0.978 (21.91) | 0.026 (0.41) | 1.018 (25.97) | 0.913 (21.60) | 0.104 (1.74) | 0.997 (24.41) | 1.003 (19.16) | -0.005 (-0.08) | 1.022 (23.92) | 0.967 (18.26) | 0.055 (0.78) |
| SMB | 0.155 (2.68) | -0.045 (-0.73) | 0.201 (2.29) | 0.151 (2.56) | -0.025 (-0.42) | 0.176 (1.96) | 0.154 (2.19) | -0.049 (-0.61) | 0.204 (1.70) | 0.156 (2.19) | -0.030 (-0.44) | 0.186 (1.74) |
| HML | 0.077 (1.24) | 0.472 (5.94) | -0.395 (-4.81) | 0.091 (1.44) | 0.401 (4.18) | -0.309 (-2.58) | 0.098 (1.38) | 0.401 (3.64) | -0.302 (-2.20) | 0.132 (1.68) | 0.265 (2.78) | -0.133 (-1.08) |
| UMD | | | | 0.035 (0.87) | -0.171 (-2.22) | 0.206 (2.90) | | | | 0.033 (0.88) | -0.193 (-2.75) | 0.227 (3.33) |
| RMW | | | | | | | -0.011 (-0.14) | 0.016 (0.16) | -0.027 (-0.19) | -0.021 (-0.25) | 0.100 (1.03) | -0.121 (-0.86) |
| CMA | | | | | | | -0.042 (-0.32) | 0.155 (1.06) | -0.197 (-0.95) | -0.062 (-0.43) | 0.158 (1.00) | -0.221 (-0.94) |
| STR | | | | | | | | | | -0.053 (-0.89) | -0.058 (-1.05) | 0.007 (0.06) |
| LTR | | | | | | | | | | -0.016 (-0.17) | 0.096 (0.77) | -0.111 (-0.63) |
| LIQ | | | | | | | | | | -0.022 (-0.52) | -0.025 (-0.37) | 0.004 (0.05) |
| Adj. R ² | 0.789 | 0.693 | 0.126 | 0.789 | 0.716 | 0.183 | 0.788 | 0.693 | 0.126 | 0.787 | 0.719 | 0.183 |
| N months | 282 | 282 | 282 | 282 | 282 | 282 | 282 | 282 | 282 | 282 | 282 | 282 |

Table 3. 5: Performance of Trading Strategies: Conditional Factor Models

The table reports the performance estimates of trading strategies defined using the return prediction model. We use extended conditional factor models to obtain the alpha and factor exposure estimates for Long, Short, and Long-Short portfolios. These portfolios are defined in Table 3.4. The conditional factor models contain some combination of the following factors: the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), and interactions between these factors and two U.S. economic indicators. In columns (1) to (3), we report estimates from the conditional model of Lettau and Ludvigson (2001b). This factor model includes the RMRF, SMB, HML, and UMD factors, and the interactions between these four factors and the mean-free lagged *cay* residual of Lettau and Ludvigson (2001a, 2001b). In columns (4) to (6), we report alpha estimates and factor exposures from a conditional model that includes the RMRF, SMB, HML, and UMD factors, and the interactions between these four factors and the U.S. recession dummy variable *REC*. The *REC* variable is set to one for quarters in which the U.S. economy experienced a contraction according to the NBER. In columns (7) to (9), we use a 12-factor model to adjust for risk, which contains the main four factors (RMRF, SMB, HML, UMD) and the interactions of these factors with both the *cay* residual and the NBER recession indicator. For each factor model, we report the estimates of monthly alphas as well as the factor exposures. The *t*-statistics are computed after adjusting for Newey-West (1987) standard errors and brackets below the estimates. The estimation period is from July 1995 to December 2018.

| Factor | Portfolio | | | | | | | | |
|--------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | Long (1) | Short (2) | Long-Short (3) | Long (4) | Short (5) | Long-Short (6) | Long (7) | Short (8) | Long-Short (9) |
| Alpha | 0.429 (3.34) | -0.220 (-1.50) | 0.649 (3.35) | 0.469 (3.46) | -0.280 (-1.66) | 0.749 (3.56) | 0.401 (2.99) | -0.311 (-1.84) | 0.712 (3.30) |
| RMRF | 1.055 (26.35) | 0.917 (21.22) | 0.137 (2.48) | 1.001 (23.27) | 0.927 (18.76) | 0.074 (1.11) | 1.044 (23.73) | 0.932 (19.27) | 0.112 (1.75) |
| SMB | 0.142 (2.44) | 0.040 (0.63) | 0.102 (1.15) | 0.121 (1.95) | -0.058 (-0.88) | 0.179 (1.81) | 0.114 (1.83) | 0.008 (0.12) | 0.105 (1.05) |
| HML | 0.045 (0.77) | 0.268 (4.65) | -0.224 (-2.67) | 0.108 (1.60) | 0.389 (3.61) | -0.281 (-2.75) | 0.075 (1.11) | 0.281 (3.79) | -0.206 (-1.99) |
| UMD | 0.037 (0.84) | -0.237 (-4.05) | 0.274 (3.47) | 0.076 (1.71) | -0.091 (-1.00) | 0.168 (1.76) | 0.079 (1.36) | -0.154 (-2.11) | 0.233 (2.20) |
| RMRF \times <i>cay</i> | -2.821 (-1.20) | 1.132 (0.37) | -3.953 (-1.12) | | | | -3.555 (-1.48) | 1.410 (0.45) | -4.966 (1.32) |
| SMB \times <i>cay</i> | 3.738 (1.11) | -7.801 (-2.04) | 11.539 (2.45) | | | | 3.420 (1.04) | -8.080 (-2.03) | 11.501 (2.39) |
| HML \times <i>cay</i> | 10.022 (3.36) | 15.045 (3.41) | -5.022 (-0.99) | | | | 8.816 (2.66) | 13.411 (3.07) | -4.594 (-0.84) |
| UMD \times <i>cay</i> | -2.552 (-0.79) | 5.636 (1.17) | -8.189 (-1.36) | | | | -2.968 (-0.89) | 3.835 (0.90) | -6.804 (-1.13) |
| RMRF \times <i>REC</i> | | | | 0.077 (0.94) | -0.240 (-2.85) | 0.317 (2.60) | 0.059 (0.73) | -0.246 (-2.71) | 0.306 (2.48) |
| SMB \times <i>REC</i> | | | | 0.247 (1.74) | -0.022 (-0.14) | 0.269 (1.09) | 0.210 (1.47) | -0.006 (-0.04) | 0.216 (0.80) |
| HML \times <i>REC</i> | | | | -0.142 (-1.32) | 0.131 (0.87) | -0.273 (-1.72) | -0.175 (-1.63) | 0.117 (0.77) | -0.292 (-1.76) |
| UMD \times <i>REC</i> | | | | -0.069 (-1.06) | -0.334 (-2.87) | 0.264 (2.18) | -0.072 (-1.02) | -0.297 (-2.71) | 0.225 (1.73) |
| Adj. R ² | 0.800 | 0.732 | 0.205 | 0.793 | 0.730 | 0.199 | 0.803 | 0.742 | 0.218 |
| <i>N</i> months | 281 | 281 | 281 | 281 | 281 | 281 | 281 | 281 | 281 |

Table 3. 6: Long Horizon Predictability and Trading Strategy Performance

The table reports the h -quarter-ahead 9 and 12-factor alpha estimates from trading strategies. We estimate monthly alpha estimates for the trading strategies corresponding to the h -quarter-ahead recursive predictability regression of the form: $Y_{j,t+h-1} = \alpha_j + X_{j,t-1}^{MEI} \delta_1 + X_{j,t-2} \delta_2 + X_{USA,t-2} \delta_3 + \log(1 + D/P)_{j,t-1} \delta_4 + \varepsilon_{j,t+h-1}$, where $h = \{1, 2, 4, 8\}$ to avoid look-ahead bias. The dependent variable is the h -quarter-ahead characteristic-adjusted return of state portfolio j . For $h > 1$, the estimation period decreases by $h - 1$ quarters. For each h , based on predictive state portfolio return, we form the Long, Short, and Long-Short portfolios. These portfolios are defined in Table 3.4. The alpha estimates are generated using both unconditional and conditional factor models. Panel A reports the unconditional factor model controlling for the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), the operating profitability factor (RMW), the investment factor (CMA), two reversal factors (short-term reversal (STR), long-term reversal (LTR), and the liquidity factor (LIQ). In panel B, we estimate the h -quarter-ahead 12-factor alpha. This factor model includes the RMRF, SMB, HML, and UMD factors, and the interactions between these four factors and the mean-free lagged *cay* residual of Lettau and Ludvigson (2001a, 2001b) and NBER recession indicator. The NBER recession indicator is set to one for quarters in which the U.S. economy experienced a contraction according to the NBER. 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 July 1995 to December 2018.

| Panel A: Monthly unconditional alpha estimates | | | | |
|--|-------------------|-------------------|-------------------|-------------------|
| Portfolio | Quarters Ahead | | | |
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ |
| Long | 0.532 (3.89) | 0.534 (4.14) | 0.098 (0.73) | 0.016 (0.12) |
| Short | -0.232 (-1.51) | -0.158 (-0.97) | -0.209 (-1.33) | -0.315 (-1.81) |
| Long-Short | 0.764 (4.10) | 0.692 (3.94) | 0.307 (1.61) | 0.331 (1.40) |
| N months | 282 | 279 | 273 | 261 |
| Panel B: Monthly conditional alpha estimates | | | | |
| Portfolio | Quarters Ahead | | | |
| | $h = 1$ | $h = 2$ | $h = 4$ | $h = 8$ |
| Long | 0.401 (2.99) | 0.393 (3.24) | 0.077 (0.65) | -0.088 (-0.70) |
| Short | -0.311 (-1.84) | -0.124 (-0.74) | -0.227 (-1.39) | -0.314 (-1.82) |
| Long-Short | 0.712 (3.30) | 0.517 (2.49) | 0.304 (1.52) | 0.226 (1.00) |
| N months | 282 | 279 | 273 | 261 |

Table 3. 7: Visibility Subsamples: Alpha Estimates and Subsequent Correction

The table presents emotional exuberance-driven geography-based trading strategy alpha estimates and subsequent corrections for firms with Low (High) local visibility. The visibility subsamples are constructed using Hong, Kubik, and Stein (2008) visibility index. We define the visibility index as the residual from a regression of the log number of shareholders on the log of total sales. The visibility regression is estimated yearly. The Low (High) visibility firms belong to the bottom (top) tercile based on local visibility index. In Panel A, we report the alpha estimates of Long, Short, and Long-Short geography-based portfolios for Low (High) visibility firms. The portfolios are defined in the caption of Table 3.4. In Panel B, we estimate h -quarter-ahead alpha estimates and $h = 1$ represents baseline alphas based on visibility index. 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 July 1995 to December 2018.

| Panel A: Initial mispricing ($h = 1$) | | |
|---|-------------------|-------------------|
| Portfolio | Visibility | |
| | Low | High |
| Long | 0.386 (1.87) | 0.426 (2.42) |
| Short | -0.372 (-1.45) | -0.006 (-0.03) |
| Long-Short | 0.757 (2.56) | 0.432 (1.74) |
| Panel B: Subsequent correction ($h \geq 1$) | | |
| h | Low | High |
| 1 | 0.757 (2.56) | 0.432 (1.74) |
| 2 | 0.624 (2.23) | 0.269 (1.00) |
| 4 | 0.499 (1.63) | 0.262 (1.00) |
| 8 | 0.373 (0.99) | 0.235 (0.86) |

Table 3. 8: State Portfolio Characteristics and State Demographics

The table shows the average state characteristics and demographics across four portfolios – Long, Others, Short, and Long-Short. The portfolio construction is defined in Table 3.4 and the details are available in the caption of that table. 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 July 1995 to December 2018.

| State characteristics and demographics | Portfolio | | | |
|--|-----------|--------|--------|--------------------|
| | Long | Others | Short | Long-Short |
| State MEI | 0.192 | 0.170 | 0.148 | 0.044 (3.04) |
| State LM | -0.286 | -0.311 | -0.319 | 0.033 (2.19) |
| State HN | 0.215 | 0.195 | 0.188 | 0.027 (2.01) |
| State Inc Gr | 0.055 | 0.042 | 0.032 | 0.023 (6.97) |
| State Unemp Rate | 1.029 | 0.982 | 0.947 | 0.082 (3.04) |
| State h_y | -0.066 | -0.059 | 0.032 | -0.098 (-3.83) |
| $\log(I+D/P)$ | 0.010 | 0.017 | 0.029 | -0.019 (-13.45) |
| SAI | -0.024 | -0.032 | -0.023 | -0.001 (-0.01) |
| M_AGE | 35.919 | 37.074 | 37.315 | -1.396 (-3.61) |
| EDU | 0.290 | 0.279 | 0.264 | 0.026 (3.19) |
| MALE | 0.983 | 0.961 | 0.954 | 0.029 (6.60) |
| MARRIED | 0.529 | 0.513 | 0.493 | 0.036 (6.69) |
| MINORITY | 0.145 | 0.198 | 0.253 | -0.108 (-8.89) |
| URBAN | 0.783 | 0.733 | 0.709 | 0.074 (3.62) |
| TOTPOP(m) | 5.452 | 6.656 | 4.513 | 0.939 (1.85) |
| INCOME(m) | 0.050 | 0.048 | 0.045 | 0.005 (6.23) |
| POVERTY | 0.120 | 0.132 | 0.151 | -0.031 (-6.54) |

Table 3. 9: Panel Predictive Regression Estimates: Tone, Sentiment, Local Optimism, and Local Bias

The table reports the result from panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-1}^{MEI} \delta_1 + X_{j,t-2} \delta_2 + X_{USA,t-2} \delta_3 + \log(1 + D/P)_{j,t-1} \delta_4 + X_{j,t-1}^{Tone} \delta_5 + X_{j,t-1}^{Sent} \delta_6 + X_{j,t-1}^{SBO} \delta_7 + X_{j,t-1}^{SLI} \delta_8 + X_{j,t-1}^{RATIO} \delta_9 + \varepsilon_{j,t}$. Specifically, we predict the quarterly state portfolio return in quarter t using lagged state- and macroeconomic-level variables measured in quarter $t - 1$ or $t - 2$. The dependent variable $Y_{j,t}$ is the difference between the state return and a benchmark return which is the characteristic-adjusted return computed using the Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) method. The row vectors $X_{j,t-1}^{MEI}$, $X_{j,t-1}^{Tone}$, $X_{j,t-1}^{Sent}$, $X_{j,t-1}^{SBO}$, $X_{j,t-1}^{SLI}$, and $X_{j,t-1}^{RATIO}$ contain the state market emotion index, tone, sentiment, local optimism, local economic activity forecast, and local bias-based measures. In column (1), we include two tone measures. From column (2) to (5), we control for sentiments, local optimism, economic activity forecast, and local bias. In column (6), we exclude Korniotis and Kumar (2013) state-level return predictors. In column (7), we include all the predictors. To derive tone measures, we use Loughran and McDonald (2011, LM) and Henry (2008, HN) positive and negative word lists. Tone is the ratio of the difference between positive and negative word counts to the total of positive and negative word counts. The sentiment measures are the Baker and Wurgler (2006) investor sentiment index and University of Michigan's Consumer Confidence Index. We follow Chhaochharia et al. (2019) and proxy local optimism by small business optimism index. Following Smajlbegovic (2019), we use economic activity forecast proxied by state leading index of Crone and Clayton-Matthews (2005). We follow Hong, Kubik, and Stein (2008) to derive the local bias-based RATIO measure which is the total book value of equity in a region to aggregate income of that region. The row vectors $X_{j,t-2}$ and $X_{USA,t-2}$ contain the state- and U.S.-level predictors, respectively. The t -statistics are reported in parentheses beneath the estimates use serial and cross-sectional correlation adjusted Driscoll and Kraay (1998) standard errors. The estimation period is from 1990 to 2018.

| Predictor | Benchmark for Computing Residual Return | | | | | | |
|--|---|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| | DGTW (1) | DGTW (2) | DGTW (3) | DGTW (4) | DGTW (5) | DGTW (6) | DGTW (7) |
| <i>Main Predictor</i> | | | | | | | |
| State MEI | 0.018 (2.08) | 0.019 (2.16) | 0.021 (2.38) | 0.021 (2.47) | 0.020 (2.39) | 0.018 (2.44) | 0.018 (2.35) |
| <i>State-level Business Cycle Predictors</i> | | | | | | | |
| State Inc Gr | 0.019 (0.20) | 0.009 (0.09) | 0.007 (0.07) | 0.013 (0.14) | 0.013 (0.14) | | 0.005 (0.05) |
| State Rel Un | 0.012 (1.94) | 0.012 (1.95) | 0.014 (2.29) | 0.013 (1.91) | 0.012 (1.95) | | 0.013 (2.15) |
| State hy | -0.006 (-0.66) | -0.007 (-0.73) | -0.007 (-0.79) | -0.006 (-0.61) | -0.006 (-0.68) | | -0.007 (-0.76) |
| <i>Tone-based Predictors</i> | | | | | | | |
| State LM | 0.001 (0.04) | | | | | 0.001 (0.13) | 0.002 (0.17) |
| State HN | 0.009 (0.64) | | | | | 0.005 (0.41) | 0.003 (0.27) |
| <i>Sentiment-based Predictors</i> | | | | | | | |
| Investor Sentiment | | 0.009 (0.87) | | | | 0.008 (0.80) | 0.008 (0.77) |
| Consumer Confidence Index | | 0.076 (2.71) | | | | 0.076 (2.85) | 0.076 (2.90) |
| Small Business Optimism | | | 0.001 (1.33) | | | 0.001 (0.68) | 0.001 (1.06) |
| State Leading Index | | | | 0.001 (0.35) | | 0.001 (0.21) | 0.001 (0.24) |
| <i>Local Bias-based Predictor</i> | | | | | | | |
| RATIO | | | | | -0.056 (-0.29) | -0.092 (-0.50) | -0.100 (-0.54) |
| <i>Other U.S.-level Predictors</i> | | | | | | | |
| Adj. R^2 | Yes | No | Yes | Yes | Yes | Yes | Yes |
| N obs | 5028 | 5028 | 5028 | 5028 | 5028 | 5028 | 5028 |

Table 3. 10: Panel Predictive Regression Estimates: Robustness Tests

The table summarizes the results from various robustness checks. The results are from panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-1}^{MEI} \delta_1 + X_{j,t-2} \delta_2 + X_{USA,t-2} \delta_3 + \log(1 + D/P)_{j,t-1} \delta_4 + \varepsilon_{j,t}$. For brevity, we only report the estimates of the main state market emotion index variable. The details of the regressions are identical to those estimated in column (4) of Table 3.3 and are available in the caption of that table. Test (1) is the baseline coefficient presented in Table 3.3 column (4). In test (2), we exclude two large states – California and New York. From tests (3) to (6), we exclude each individual regions based on U.S. Census. In test (7), we exclude states that are oil producers. Oil producing states are those that produced more than 500 barrels of oil per day in 2007 and include California, Texas, and Louisiana. In test (8), we exclude 15 oil-consuming east coast states (see Chhaochharia et al., 2020). The dominant firm states in test (9) are Arkansas (Walmart) and Washington (Amazon and Microsoft). In tests (10) and (11) we use two alternative measures of market emotion index. The first alternative MEI measure is $Net\ MEI_{j,t} = \frac{Excitement_{j,t} - Anxiety_{j,t}}{Total\ Words_{j,t}}$; and the second one is $Total\ MEI_{j,t} = \frac{(Excitement_{j,t} + Mania_{j,t}) - (Anxiety_{j,t} + Blame_{j,t} + Denial_{j,t} + Guilt_{j,t} + Panic_{j,t})}{Total\ Words_{j,t}}$. Finally, in test (12) we use region and year fixed effects. The t -statistics are reported in parentheses beneath the estimates use serial and cross-sectional correlation adjusted Driscoll and Kraay (1998) standard errors. The estimation period is from 1990 to 2018.

| Test | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| (1) Baseline | 0.020 (2.35) | | | | | | | | | | | |
| (2) Remove CA and NY | | 0.022 (2.31) | | | | | | | | | | |
| (3) Exclude North-East | | | 0.022 (2.46) | | | | | | | | | |
| (4) Exclude Mid-West | | | | 0.019 (2.17) | | | | | | | | |
| (5) Exclude South | | | | | 0.017 (2.14) | | | | | | | |
| (6) Exclude West | | | | | | 0.035 (1.91) | | | | | | |
| (7) Exclude Oil Producers | | | | | | | 0.024 (2.63) | | | | | |
| (8) Exclude Oil Consumers | | | | | | | | 0.022 (1.75) | | | | |
| (9) Exclude Dominant Firm State | | | | | | | | | 0.025 (2.88) | | | |
| (10) Net MEI | | | | | | | | | | 0.414 (2.00) | | |
| (11) Total MEI | | | | | | | | | | | 0.326 (1.91) | |
| (12) Region Fixed Effects | | | | | | | | | | | | 0.019 (2.18) |

Table 3. 11: Trading Strategy Performance Estimates: Robustness Tests

The table includes alpha estimates from various robustness tests. We report alpha estimates from various factor models and the corresponding t -statistics in parentheses below the estimates. Across all the panels, we use conditional factor model that includes the market (RMRF), size (SMB), value (HML), and momentum (UMD) factors, and the interactions between these four factors and the mean-free lagged *cay* residual of Lettau and Ludvigson (2001a, 2001b) and NBER recession indicator. The NBER recession indicator is set to one for quarters in which the U.S. economy experienced a contraction according to the NBER. In Panel A, we use a variety of prediction models to obtain the state rankings and form the Long and Short portfolios. In column (1), we report the alpha estimate by using standardized market emotion index. To generate a standardized MEI, we generate a series of MEI with mean 0 and standard deviation of 1. In columns (2) and (3), we estimate the predictive regressions using alternative measures of local market emotion index and these are defined in the caption of Table 3.10. In column (4) we use a qualitative model that is based on a standardized market emotion index and state economic activity index of Korniotis and Kumar (2013). To compute the state economic activity index, we add the standardized values of state income growth and state housing collateral ratio, subtract the standardized value of relative unemployment, and divide this sum by three. In panel B column (1), we use a prediction model including state-level market emotion index and the U.S. predictors excluding all other state-level predictors. In column (2) we exclude U.S.-level macroeconomic predictors. In column (3), we include two tone measures constructed using Loughran and McDonald (2011) and Henry (2008) positive and negative word lists. Column (4) uses a prediction model including tones and Baker and Wurgler (2006) investor sentiment and University of Michigan Consumer Confidence Indices. In Panel C, we report the alpha estimates for various subsamples defined based on firm attributes. Specifically, we exclude stocks of financial firms (column (1)), growth stocks (book-to-market in the bottom one fifth) (column (2)), stocks with price less than \$5 (column (3)), and small stocks (size less than 20th percentile of market capitalization) (column (4)). 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 July 1995 to December 2018.

| Panel A: Alpha estimates from other predictability models | | | | |
|---|-------------------|-------------------|-------------------|--------------------------|
| Portfolio | Std. MEI (1) | Net MEI (2) | Total MEI (3) | Qualitative Model (4) |
| Long | 0.241 (1.73) | 0.224 (1.65) | 0.276 (2.10) | 0.287 (2.07) |
| Short | -0.352 (-2.30) | -0.245 (-1.58) | -0.436 (-2.83) | -0.321 (-1.81) |
| Long-Short | 0.593 (2.83) | 0.469 (2.16) | 0.712 (3.25) | 0.608 (2.59) |

Table 3. 11: Continued

| Panel B: Alpha estimates from other predictability models | | | | |
|---|------------------------------|---------------------------|--------------------------|---------------------------------|
| Portfolio | Exclude State Bus Cyc (1) | Exclude US Bus Cyc (2) | Including Tones (3) | Including Tones and Sent (4) |
| Long | 0.118 (0.74) | 0.305 (2.53) | 0.372 (2.70) | 0.284 (1.95) |
| Short | -0.547 (-3.62) | -0.351 (-2.14) | -0.317 (-2.30) | -0.194 (-1.32) |
| Long-Short | 0.665 (2.80) | 0.656 (3.17) | 0.689 (3.51) | 0.478 (2.31) |
| Panel C: Firm attribute-based subsample alpha estimates | | | | |
| Portfolio | Exclude Fin Firms (1) | Exclude Growth (2) | Exclude Low Price (3) | Exclude Small (4) |
| Long | 0.402 (2.79) | 0.634 (3.23) | 0.448 (3.29) | 0.412 (3.05) |
| Short | -0.246 (-1.25) | -0.120 (-0.62) | -0.280 (-1.64) | -0.304 (-1.81) |
| Long-Short | 0.648 (2.84) | 0.754 (2.87) | 0.728 (3.32) | 0.716 (3.31) |

Chapter 4

An Emotion-imbued Behavioral Factor Model

4.1 Introduction

The stock market is a highly emotional environment. Powerful investor emotions and market dynamics are closely related (Breaban and Noussair, 2018). Kocher, Lucks, and Schindler (2019) attribute overpricing in asset markets to trader emotions such as excitement leading to lack of self-control and lower reliance on their cognitive abilities to find optimal trading strategies. Andrade, Odean, and Lin (2016) present similar experimental evidence showing how excitement triggers overpricing in asset markets leading to stock market bubbles. More generally, Breaban and Noussair (2018) find trader excitement drives prices out of line with stock fundamentals whereas anxiety-induced fear leads to price declines. However, probably due to the challenge of measuring investor emotions empirically there are no similar studies exploring the impact of such integral investor emotions as excitement and anxiety in real word asset markets in the extant literature. In this paper, we measure investor emotional states dynamically, show these are priced and distinct from other factors, and need to be included in factor models.

The recently proposed risk-behavioral factor model of Daniel, Hirshleifer, and Sun (2020, DHS) recognize the role of investor behavioral biases in asset pricing. When included in a factor model, DHS demonstrates behavioral factors can explain other traditional factors and many return anomalies. We augment the Daniel et al. (2020) factor model with an emotion-based factor. Our market-behavioral-emotional 4-factor model subsumes most conventional factors and improves the ability to explain the cross-section of average stock returns and extant asset pricing anomalies. We find that the sizable Sharpe ratio of Daniel et al. (2020) of 0.39 increases to 0.53 with the addition of our investor emotion factor during 1995-2018. We also

show that investor behavioral biases and integral emotions represent different facets of investor psychology.

Many theoretically-motivated factor models are proposed in the finance literature to account for different asset characteristics—(i) rational asset pricing theory (Fama and French, 2015; Hou, Xue, and Zhang, 2015); (ii) instrumented principal component analysis-based characteristics-sorted portfolios (Kelly, Pruitt, and Su, 2019); (iii) averaging characteristics to construct mispricing factors (Stambaugh and Yuan, 2017); and finally (iv) behavioral factors (Daniel, Hirshleifer, and Sun, 2020). However, it is an empirical question as to whether such models subsume the effect of the powerful investor emotions central to investment decision-making which are outside the scope of the conventional rational choice model (Lerner et al., 2015). To explore whether investor emotions are already captured by extant factor models, we propose an empirical model that augments the market and two recently proposed behavioral factors of Daniel et al. (2020) with an investor emotion factor. We show that our emotion-imbued behavioral factor model makes an enhanced contribution in explaining the cross-section of average realized returns.

The motivation for including emotion in our empirical model is in part inspired by the recent emotion in decision-making literature, and psychology-based object relations theory. Emotions are fundamental and have a potent and pervasive impact on decision making (Lerner et al., 2015). Individuals also form emotional relationships, both conscious and nonconscious, with an object, item, person, or place – known as ‘object relations’ based on their early infant experiences (Auchincloss and Samberg, 2012) – which influence their decision-making. We conjecture investors develop emotional relationships with the stocks they invest in, and these helps drive market prices.

Daniel et al. (2020) have recently proposed a 3-factor composite behavioral model (BF3). This model includes the market factor, and two behavioral factors – post earnings announcement drift (PEAD) and financing (FIN). These behavioral factors are motivated by investors’ limited attention and overconfidence biases. DHS argue that investors with limited attention underreact to public information such as earnings surprises leading to a predictable pattern in future abnormal returns. Also, stubborn overconfident investors’ misperceptions create mispricing and allow managers to exploit this mispricing. Their model demonstrates the importance of including behavioral measures in asset pricing models.

Emotions and market prices are related (Andrade et al., 2016; Breaban and Noussair, 2018; Kocher et al., 2019). Drawing on the emotion and decision-making, and psychology-based object-relations literature, we augment the Daniel et al. (2020) risk-behavioral model with a distinct investor emotion factor and construct a parsimonious market-behavioral-emotional 4-factor model (EBF3). In our model, the expected return of an asset in excess of the risk-free rate, denoted $E[R_i] - R_f$, is explained by 4 factors: MKT, PEAD, FIN, and an investor emotion factor (EMO) measuring the emotional utility (EU) stocks have for investors. The main contribution of our model is to introduce a distinct investor emotion factor in addition to well-known behavioral bias-based factors. We explore whether investor emotions are subsumed by behavioral biases or are complementary. We also formally test the incremental ability of investor emotions to account for many stock characteristics and to explain stock return anomalies together with behavioral factors.

Emotion is an important driver of decision making and at a sufficient level of intensity emotion can overwhelm rational decision-making (Lowenstein and Lerner, 2003). Lerner et al. (2015) propose an emotion-imbued choice model that shows how the impact of emotions on decision-making is beyond the scope of rational decision-making. Recent finance and asset pricing literature provide evidence linking incidental emotions – emotions unrelated to a decision – such as mood, sentiment, and weather to asset prices (see, for example, Saunders, 1993; Hirshleifer and Shumway, 2003; Edmans, Garcia, and Norli, 2007; Tetlock, 2007; Hirshleifer, Jiang, and DiGiovanni, 2020; Obaid and Pukthuanthong, 2021; Edmans et al., 2021). We add to this strand of literature by focusing on integral emotions such as excitement and anxiety that are more fundamental and powerful (see Lerner et al., 2015) in driving decisions.

Following Fama and French (1993, 2015), we construct our emotion beta factor (EMO) from a 2-by-3 sort on size and emotion beta. We employ the context-specific emotion keyword dictionaries of Taffler, Agarwal, and Obring (2021) and count excitement- and anxiety-related words from news articles to construct a novel market emotion index (MEI). Our stock-specific emotion betas measure the sensitivity of stock returns to changes in the market emotion index. We focus on excitement and anxiety because these two emotions as experimental research shows are manifest in experimental stock market (e.g., Andrade, Odean, and Lin, 2016; Breaban and Noussair, 2018) and investors' risk preferences and beliefs (see, for example,

Kuhnen and Knutson, 2011) as well as encapsulating a range of other emotions.¹ We collect newspaper articles about the state of the stock market from January 1990 to December 2018 from twenty-one national- and local-level newspapers covered by the Nexis and ProQuest databases using keywords such as ‘Stock Index’, ‘S&P 500’, and ‘Stock Market’. We use newspaper articles as our data source as media reflects the way investors perceive the stock market and a multitude of evidence finds that media and the stock market are closely related (e.g., Tetlock, 2007; Engelberg and Parsons, 2011; Dougal et al., 2012).

Following Henry and Leone (2016), we use our word counts to generate our market emotion index (MEI) as the ratio of difference between excitement and anxiety words to the total of excitement and anxiety words. We then, estimate the stock emotion beta by running a 60-month rolling regression of excess stock returns on our market emotion index, Fama-French factors – market, size, and value, momentum, Hou et al. (2015) investment and profitability, and Pastor and Stambaugh (2003) liquidity factors. We work with the absolute value of emotion beta rather than its valency as emotions with the same valence can have opposing effects (Lerner and Keltner, 2000, 2001). Keltner and Lerner (2010) document, for example, that fear breeds pessimism and anger produces optimism even though both fear and anger are generated from the same negative valence. Bin Hasan, Kumar, and Taffler (2021) also demonstrate empirically that it is the strength of investors’ emotional relationship with a stock which is priced not its valency. Thus, we focus on absolute stock emotion sensitivity rather than the sign of its emotion beta.²

Barillas and Shanken (2018) suggest that to compare models with traded factors we need to examine a model’s ability to price the returns of both test assets and traded factors. We first run spanning tests to examine how well other traded factors explain the performance of our emotion-imbued behavioral factor model, and vice-versa. We find that our composite

¹ We count emotion words across seven emotion dimensions such as ‘excitement’, ‘anxiety’, ‘guilt’, ‘denial’, ‘mania’, and ‘panic’ using Taffler et al.’s (2021) seven keyword dictionaries. We use principal component analysis and find that all seven dimensions collapse into two factors. Excitement drives the first factor whereas anxiety drive the second. We find qualitatively similar results when we use these factors in place of excitement and anxiety.

² The psychological affective circumplex model describes emotional intensity as ‘arousal’ which increases with absolute value of valence (Posner et al., 2005). This emotional arousal at sufficient levels of intensity overwhelms cognitive processing (Loewenstein and Lerner, 2003). Bin Hasan et al. (2021) also show that the strength of the investors’ emotional relationships with stocks drive investor decision-making which significantly predicts future stock returns.

model prices many of the traded factors proposed in the literature. On the other hand, other factor models cannot fully explain the abnormal returns associated with our EBF3 model.

We then explore the extent to which our model explains well-known return anomalies constructed by sorting on different stock characteristics. In this, we closely follow Hou et al. (2015) in the list of anomalies we explore. Following Daniel et al. (2020), we also group anomalies into short- and long-horizon categories. We compare the performance of our 4-factor model with the following models prominent in the literature: the Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Black, 1972, CAPM), Fama and French 3-factor Model (1993, FF3), Carhart (1997, Carhart4), Fama and French 5-factor model (2015, FF5), Hou, Xue, and Zhang q -factor model (2015, HXZ4), Barillas and Shanken 6-factor model (2018, BS6), and 4-factor model of Stambaugh and Yuan (2017, SY4).

We find none of the models in the spanning tests we consider explain our emotion beta factor. Our composite market-behavioral-emotional factor model largely subsumes the factors used in other factor models. We also find that across the 12 short-horizon anomalies we test, our model fully captures all anomalies, i.e., none have significant alphas. In contrast, 11 anomalies have significant CAPM and FF3 alphas, the Carhart4 and FF5 models have three significant alphas, and HXZ4 and BS6 have two and three significant anomaly alphas respectively. SY4 has one significant alpha. Mean $|\hat{\alpha}|$ is lower for our composite model than for the CAPM, FF3, Carhart4, FF5, and SY4 models. Finally, the Gibbons, Ross, and Shanken (1989, GRS) F-test fails to reject the hypothesis that our emotion-imbued behavioral factor model alphas are jointly zero.

The EBF3 model also explains long-horizon anomalies relatively well with only three out of the 22 significant alphas. For other models, the number of significant alphas is 14 (CAPM), 13 (FF3), 11 (Carhart4), 7 (BS6), 6 (HXZ4), 5 (FF5), and 2 (SY4) respectively. The GRS F-test that the long-horizon anomaly portfolio alphas are jointly zero is rejected for all the models except for the non-parsimonious SY4 model.

Across all 34 anomalies, our emotion-imbued behavioral factor model has only 3 significant composite-model alphas. In comparison, there are 25 CAPM and 24 FF3 significant alphas, 14 Carhart significant alphas, 10 BS6, 8 significant FF5 and HXZ4 alphas, and 3 SY4 significant alphas. Except for SY4, EBF3 has the smallest mean $|\hat{\alpha}|$ and mean $|t\text{-statistic}|$, and lowest GRS F -statistic. However, SY4 is sensitive to the way in which it is developed, and

when conventionally constructed becomes closer to Hou et al.'s (2015) q -factors (Hou et al. 2019). Our market-behavioral-emotional model therefore outperforms both extant factor models in explaining a large set of anomalies studied by Hou et al. (2015). This evidence is consistent with the hypothesis that many existing anomalies, such as momentum, profitability, value, investment and financing, and intangibles, can be attributed to systematic and behavioral- and emotion-based mispricing. Overall, our results show that investor emotion is a separate priced factor, and demonstrate the need to include this together with behavioral factors in asset pricing models.

The main contributions of this paper are to demonstrate investor integral emotions are priced, and to introduce an emotion factor into an empirical asset pricing model. Our study contributes to several strands of the literature. First, it introduces the emotions in decision making psychology and object relations theory into empirical finance by showing the impact of investor emotions on their decision making. Second, our paper is related to those of Fama and French (2015), Hou Xue, and Zhang (2015), Hou et al. (2019), and Daniel et al. (2020) which all introduce, construct, and compare different factor models. We extend this line of research in three ways – one, by introducing investor emotion as a factor that influences investors portfolio decisions; two, we augment the BF3 risk-behavioral model of Daniel et al. (2020) by adding this factor; three, use the resulting EBF3 model to price a wide range of anomalies.

Third, more broadly we contribute to the literature exploring the relationship between the media and the stock market. This shows, for example, media narratives impact aggregate market outcomes (Dougal et al., 2012), local media coverage affects local trading (Engleberg and Parsons, 2011), and media tone impacts stock prices (e.g., Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008; Hillert, Jacobs, and Müller, 2014). We add to this body of work by developing a market emotion index using news articles about the stock market and show that this can be used to construct a distinct asset pricing factor.

Our paper is also related to the recent paper of Barberis, Jin, and Wang (2021) who draw on key ingredients of prospect theory such as investor preference and narrow framing to explain stock market anomalies. Our effort is to combine behavioral psychology and emotional psychology which complement each other in describing asset prices. Both studies provide different psychology-based predictions about factor and anomaly returns.

The rest of the paper is organized as follows. Section 2 provides the motivation behind the construction and inclusion of emotion as a factor in a factor model. Section 3 explains the construction of our emotion factor, compares different prominent asset pricing factors, and uses spanning regressions to identify the distinctiveness of different factor models. Section 4 presents empirical results related to explaining two sets of anomalies divided in terms of short- and long-horizon predictability. Section 5 concludes.

4.2 Motivation

Our motivation for including emotion in a factor model is driven by the psychology of emotion, object relations, and news and stock returns literatures. Daniel, Hirshleifer, and Subrahmanyam (2001) show that return comovement can result from commonality in investor decisions errors. We utilize this line of reasoning by introducing investor emotion that, together with behaviorally-motivated factors, can be used to construct and incorporated in a factor model to improve our ability to describe the cross-section of expected returns. Our novel emotion factor captures investor emotions reflected in media narratives about the state of the stock market which complements behavioral explanations such as investor inattention and overconfidence.

Our emotion factor focuses on investors' emotional relationships with the stocks they invest in that we demonstrate drive their investment decision-making in a systematic manner. We propose that just as firms exposed to systematic risk and/or behavioral factors earn an associated risk premium, firms with which investors have a strong emotional attachment and derive emotional utility from should also earn an additional rate of return. Fama and French (1993, 2015) construct risk factors and Daniel et al. (2020) behavioral factors where the former captures risk exposures and the latter irrationality. We supplement both these risk and behavioral factors with an investor emotion factor to capture stock emotional utility.

We hypothesize that investors experience integral emotions such as that of excitement and anxiety and enter into emotional relationships with their stocks that make their decision-making predictable. For example, when the market is doing well, and excitement is high trend chasers or momentum investors will react to past performance and continue to do so by pushing prices up. When the market is bearish and anxiety dominates, contrarian investors will become active and drive up the price. In both cases the stock price is impacted in a predictable way. This predictability could explain different return comovement mechanisms. The effects of

integral emotions such as, excitement and anxiety, operate both at conscious and nonconscious levels (Lerner et al., 2015). They are very difficult to disentangle from decision-making process (Rozin, Millman, and Nemeroff, 1986), are remarkably influential even in the presence of cognitive information (Loewenstein, 1996), and can easily override rational courses of action (Loewenstein et al., 2001).

We draw on the emotion-imbued choice model (Lerner et al., 2015) to identify ways in which emotion enters choice processes that affect conscious and nonconscious decision-making. Integral emotions that are entirely outside the scope of rational choice models permeate decision-making. Figure 4.1, adapted from Lerner et al. (2015), illustrates this diagrammatically in the case of the investor decision making. Investors' integral emotions such as excitement and anxiety along with risk perceptions and asset fundamentals direct their decision-making both conscious and nonconscious ways. Thus, the ultimate decision to buy, hold, or sell a stock is a combination of the investor's emotion-modified risk perception and subjective valuation of future outcomes (Figure 4.1, line D). This affects the demand and/or supply of securities and drives the asset prices.

Empirical evidence shows that incidental emotions induced by such things as weather (Saunders, 1993; Hirshleifer and Shumway, 2003), sports sentiment (Edmans et al., 2007), seasonality (Hirshleifer et al., 2020), or music (Edmans et al., 2021) enter into the economic decision-making by altering investor mood. Incidental emotions are less context specific (Watson and Tellegen, 1985) than deeper integral emotions. Importantly, individuals can minimize the impact of incidental emotions. Schwarz and Clore (1983) find, for example, that the impact of weather on judgment and decision-making disappears when individuals are made aware of this. In this way, a simple reminder to attribute mood to its source can eliminate the effects of incidental emotions. Integral emotions which are largely nonconscious, however, are more powerful as often not directly accessible, and enter into the decision-making process directly as well as indirectly. We contribute by formally introducing integral emotions to investor decision-making.

The intensity of integral emotions progressively takes over (Loewenstein, 1996) and dominates rational decision-making. Loewenstein and Lerner (2003) suggest that at sufficient levels of intensity, integral emotions overwhelm cognitive processing and often propel behavior in directions that are more satisfying to individuals than being economically optimal (see, for example, Simon, 1955; Conlisk, 1996). The economics literature (see, for example,

Kaufman, 1999; Hanoch, 2002) argues that with the help of emotions the individual makes satisfying decisions under conditions of bounded rationality. Further, Caplin and Leahy (2001) show individuals value and try to maximize their psychological expected utility in addition to more general utility of wealth. In line with this argument, we introduce the concept of emotional utility i.e., investors' need to have an emotionally-charged relationship with a stock to invest in it, or divest from it, in the face of uncertain outcomes, in to asset pricing models.

4.3 Factor and Models

In this section, we describe the construction of our EMO factor, compare how different factors fare in generating factor premia, their associated correlations, and examine tangency portfolio performance. Finally, we explore whether other factor models can account for our market-behavioral-emotional factor model and vice-versa.

Barillas and Shanken (2017) document that the extent to which a model prices the factors in the other model is important for model comparison. In the extant literature, the alpha in the time-series regression of an asset's excess returns on those of the factors of a model is viewed as the asset's deviation from the model. This is because a nonzero alpha indicates that it is possible to improve the Sharpe ratio by constructing a more efficient portfolio by including the given asset in the portfolio. Barillas and Shanken (2017) identify the challenge of identifying a small number of factors that correctly price returns. Taking our motivation from Barillas and Shanken (2017) in comparing the power of different asset pricing models, we run a horse race between different factor models in pricing both traded factor and test-asset returns.

We examine (i) whether prominent asset pricing factor models can explain our emotion factor (EMO), i.e., whether the alpha becomes insignificant; (ii) how our market-behavioral-and emotional model (EBF3) performs in pricing factors of those models; and finally (iii) the comparison between different factor models in explaining robust asset pricing anomalies. Following Hou et al. (2015, 2019) and Daniel et al. (2020), we compare the performance of factor models in explaining anomaly returns across several test statistics. First, we inspect the number of significant alphas that each factor models have while pricing a basket of test assets. A model's performance is poor if a large number of alphas remain significant. Second, we check the size of the average absolute alphas to assess the economic significance of mispricing. Third, we measure the average absolute t -values of alphas to investigate level of statistical

significance. Fourth, we estimate F -statistics and p -values to test whether the average t^2 of alphas for a given model are larger than the average t^2 of a given model's alpha. Finally, we compare the standard GRS F -statistics to test the null hypothesis that all alphas are jointly zero.

4.3.1 Emotion Factor Construction

We collect news articles from 21 local and national news outlets about the stock market in general to construct our emotion factor. Specifically, we collect news items about the S&P 500 index as it reflects the state of the equity market from Nexis and ProQuest databases from January 1990 to December 2018.³ Table 4.A.1 provides the list, availability, and number of articles per outlet. We use 'Stock Index', 'S&P 500', and 'Stock Market' jointly as search terms in the power search functions to identify S&P 500-specific news items. With Nexis, we only retain articles that have a relevance score equal or more than 80 percent with respect to our search terms; in ProQuest we require our search terms to be present in both the abstract and main body of the article. We exclude newswires, non-business news, and websites. This process leads us to work with 59,665 news articles. Four widely-circulated national-level U.S. newspapers – The New York Times, The Washington Post, Wall Street Journal and USA Today – cover about half of our sample articles.

We start our textual analysis process to count words by cleaning the news items. First, we convert all words to lower case. Second, we remove numerical values, punctuation, symbols, tables, and figures. Finally, in line with the natural language processing and the textual analysis literature we remove standard English stop words (e.g., a, an, and the etc.). Employing the emotional keywords dictionaries of Taffler et al. (2021), we count the excitement and anxiety words in these narratives. We work with excitement and anxiety because these are two of the most predominant human emotions explored in the experimental finance literature.⁴ Andrade et al. (2016) and Breaban and Noussair (2018) both use excitement and anxiety and relate these to highly emotional stock market events such as market bubbles. Kuhnen and Knutson (2011) also document that excitement and anxiety impact an individual's risk preferences and beliefs. Once we have these emotional word counts, we derive a market emotion index (MEI) measure following Henry and Leone (2016) as the ratio of difference

³ Nexis and ProQuest databases have good coverage of news items across the 21 news outlets from 1990 which motivates us to start our sample period from January 1990.

⁴ We also employ principal component analysis and find that 'excitement' and 'anxiety' are related to two principal factors representing all seven emotion categories.

between excitement and anxiety word counts to the total of excitement and anxiety word counts. MEI is calculated as follows:

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

where $Excitement_t$ and $Anxiety_t$ are the number of excitement and anxiety word counts in a month. Following Bali, Brown, and Tang (2017) using MEI, we then estimate our stock-specific emotion betas measuring investor emotional utility based on a 60-month rolling regression of the following form:

$$R_{i,t} - R_f = \alpha + \beta_{1,it}MKT_t + \beta_{2,it}SMB_t + \beta_{3,it}HML_t + \beta_{4,it}UMD_t + \beta_{5,it}R_{I/A,t} + \beta_{6,it}R_{ROE,t} + \beta_{7,it}LIQ_t + \beta_{it}^{MEI}MEI_t + \varepsilon_{i,t} \quad (2)$$

where $R_{i,t} - R_{f,t}$ is the excess return on stock I in month t and MKT_t , SMB_t , HML_t , and UMD_t are the Fama and French (1993) factors. The market excess returns (MKT), size (SMB), high-minus-low (HML), and winner-minus-losers (UMD) data are from Kenneth French's data library. $R_{I/A,t}$ and $R_{ROE,t}$ are the investment and profitability factors of Hou et al. (2015) and these factor returns are available from Lu Zhang's website. LIQ_t is the Pastor and Stambaugh (2003) liquidity factor and is available at Lubos Pastor's website. We use $\beta_{i,t}^{MEI}$ to derive the conditional emotion beta measure $|\beta_{i,t}^{MEI}|$. Emotion beta measures the strength of the object relationship investors feel for the stocks they invest in and derive emotional utility from. We argue emotional utility as captured by emotion beta is instrumental in investor decision-making.

To construct our emotion factor, following Fama and French (1993, 2015), Hou, Xue, and Zhang (2015, 2020), and Hou et al. (2019), at the end of each month we divide firms into two size groups (small 'S' and big 'B') based on whether market equity is below or above the NYSE median breakpoint. Independently, using NYSE firm 30% and 70% breakpoints we sort firms into one of three emotion groups (low 'L', middle 'M', or high 'H') based on firm conditional emotion beta.⁵ We form six portfolios (SL, SM, SH, BL, BM, and BH) based on

⁵ Our results are largely consistent when we use NYSE firm 20% and 80% breakpoints following Daniel et al. (2020). We report results using the 30% and 70% NYSE breakpoints as this is the conventional approach and helps control the effect of microcaps (Hou et al., 2019; Hou et al., 2020).

the intersections of size and emotion beta groups. The EMO factor return is calculated each month as the average return of the high emotional portfolios (SH and BH) minus average return of the low emotional portfolios (SL and BL), i.e., $EMO = (r_{SH} + r_{BH})/2 - (r_{SL} + r_{BL})/2$.

4.3.2 Factor Comparison

4.3.2.1 Summary Statistics, Correlations, and Ex Post Tangency Portfolios

We compare our emotion beta factor with factors used in traditional and recently enhanced factor models including the CAPM, FF3, Carhart4, FF5, HXZ4, BS6, and SY4. Monthly factor returns are downloaded from the Kenneth French, Kent Daniel, AQR, Lubos Pastor, and Lu Zhang websites.

Table 4.1 reports summary statistics for our zero-investment emotion factor along with a set of factors proposed in the literature. This shows that, over our sample period, EMO generates a premium of 0.39% per month and a monthly Sharpe ratio of 0.19.⁶ The Newey-West t -statistic testing whether the EMO premium is zero is 3.34. Comparing EMO with behavioral factors (e.g., FIN and PEAD) shows that EMO offers a relatively lower factor premium than both FIN and PEAD. EMO generates higher Sharpe ratio than FIN but marginally lower compared to PEAD. However, the FIN factor premium is not statistically significant possibly due to the sample period we have. Comparing EMO with investment factors (e.g., CMA, IVA, and RMW) shows that EMO offers a substantially higher factor premium, and comparable Sharpe ratio and t -statistic. Comparing EMO with factors based on short-horizon characteristics (e.g., MOM, and ROE), EMO offers a similar factor premium, but higher Sharpe ratio and t -statistic. Comparing EMO with factors based on mispricing (e.g., MGMT and PERF), the EMO factor offers comparable factor premium but again higher Sharpe ratio and t -statistic. Comparing EMO with the betting against beta (BAB) factor of Frazzini and Pedersen (2014) and Pastor and Stambaugh (2003) liquidity (LIQ) factors shows that EMO offers a comparable Sharpe ratio and higher t -statistic. Overall, Table 4.1 provides initial evidence that investors' obtain emotional utility from the stocks they invest in and a factor that represents such emotional utility generates economically significant factor premium.

Table 4.2 reports pairwise correlation coefficients between factors. We find that

⁶ Following Daniel et al.'s (2020) alternative factor construction procedure, using 20 and 80 percentile CRSP breakpoints, the EMO factor earns a monthly premium of 0.57 with Newey-West t -statistic of 3.57 and Sharpe ratio of 0.19.

different versions of SMB, and HML are highly correlated with correlation coefficient greater than 0.9 in most cases. The investment factors (CMA, IVA) are highly correlated ($\rho = 0.92$) and strongly correlated with the value factors (HML, HML^m) with ρ between 0.43 and 0.67. The two profitability factors (RMW and ROE) are strongly correlated with each other with ρ of 0.74. Also, the correlation of ROE with the momentum factor (MOM) is about 0.5. The MGMT factor, constructed on six investment and financing characteristics, is highly correlated with the value factor (HML) and investment factors (CMA, IVA), with ρ ranging from 0.66 to 0.76. The PERF factor, constructed on five characteristics including price momentum and profitability, is highly correlated with both the momentum factor (MOM) and profitability factors (RMW and ROE), with ρ ranging from 0.42 to 0.67. FIN is constructed using only external financing and correlated with the value factor (HML), investment factors (CMA, IVA), and management factor (MGMT) with ρ between 0.58 and 0.81. FIN is also highly correlated with profitability factors (RMW and ROE). PEAD is strongly correlated with the momentum factor (MOM) and the composite PERF factor, with ρ ranging from 0.45 to 0.53, and moderately correlated with the earnings profitability factor ROE, with $\rho = 0.19$.

Lastly, EMO factor returns are correlated with both MKT and size factors (SMB, SMB(HXZ4), and SMB(SY4)) with ρ between 0.41 and 0.45. EMO factor returns move with the market and size factors to some extent because EMO factor portfolios are constructed from investor emotions about the stock market along with the intersection of size portfolios, and thus reflects these. Importantly, EMO is effectively uncorrelated with PEAD ($\rho = 0.09$) and LIQ ($\rho = 0.14$) suggesting that the emotion factor is capturing different information.

Table 4.3 summarizes the portfolio weights, returns, and the maximum ex post Sharpe ratios that can be achieved by combining various factors to form tangency portfolios. Rows (1) and (2) show that the Fama-French three factors achieve a maximum monthly Sharpe ratio of 0.17, and adding the MOM factor increases the Sharpe ratio to 0.23 (Carhart4). Rows (3)-(6) show that the optimal combination of factors from the FF5, HXZ4, BS6, and SY4 models achieve realized monthly Sharpe ratios of 0.34, 0.32, 0.34, and 0.43, respectively. In rows (7) and (8), the two behavioral factors, FIN and PEAD, together have a Sharpe ratio of 0.24, while adding the MKT factor increases the Sharpe ratio to 0.39. However, when we combine the EMO factor with the market and the two behavioral factors, in EBF3 row (11), the Sharpe ratio is now 0.53. Thus, the Sharpe ratio of our market-behavioral-emotional 4-factor composite model is significantly higher than that of standard factor models, and all recently proposed

models.

Rows (12)-(15) show that adding different factors to our 4-factor model does not increase the Sharpe ratio reinforcing our argument that we need to augment behavioral factors with an investor emotion factor. Finally, row (16) shows that combining all factors the maximum Sharpe ratio of 0.50 excluding EMO. However, adding EMO to the ‘kitchen sink’ leads to a substantial further increase in Sharpe ratio to 0.66. Notably, all EMO portfolios indicate the need to invest more than 35 percent in the emotion beta factor.

4.3.2.2 Are Emotion and Behavioral Factors Different?

In this subsection, we examine whether our emotion-based factor is a distinct aspect of investor psychology than Daniel et al.’s (2020) behavioral factors. We run spanning regressions of the EMO factor on the two Daniel et al. (2020) behavioral factors separately and BF3, their 3-factor model, to investigate whether their behavioral factors individually or in combination explain EMO factor returns. We, then, examine whether our EMO factor alone, or in conjunction with the market factor, can account for the behavioral factors.

Panel A of Table 4.4 shows that each of the factors, MKT, FIN, and PEAD, of BF3 separately cannot explain the premium generated by the EMO factor as alpha remains economically and statistically significant. The alphas in case of spanning regressions of EMO on FIN and PEAD generates alphas of 0.56% ($t = 6.51$) and 0.35% ($t = 3.22$) respectively. Including FIN and PEAD together also cannot explain the EMO factor premium, alpha of 0.56% ($t = 6.05$). Finally, the BF3 model itself has an EMO alpha of 0.51% ($t = 5.03$). These results show that the DHS behavioral factors do not subsume the EMO factor.

In Table 4.4 Panel B, we repeat the same analysis to assess whether our EMO factor alone and together with MKT explain the BF3 behavioral model factors. We find that both EMO separately and together with MKT are unable to explain the FIN and PEAD factor premia. These results along with those of Panel A and Tables 2 and 3 demonstrate that EMO is capturing something different to investor inattention and overconfidence. As such, we conjecture our emotion factor will have asset pricing implications when included in a factor model.

4.3.3 Factor Model Comparisons

Following Fama and French (2015, 2018) and Barillas and Shanken (2017, 2018) we compare the ability of different factors models to price the returns of both test assets and traded factors. Specifically, we assess the power of our emotion-imbued behavioral factor model to price each of the factors used in extant models, and vice versa. We perform several spanning tests to compare models. Specifically, we run time-series regressions of monthly factor returns (e.g., EMO) of a model (e.g., EBF3) on the factors of other factor model (e.g., FF5) and examine the regressions alphas (intercepts). If a factor is subsumed by a set of other factors, we expect the regression alpha not to differ from zero. We present the results of spanning tests of EBF3 against the Fama-French five-factor model, the Hou, Xue, and Zhang q -factor model, the Barillas and Shanken 6-factor model, and the Stambaugh and Yuan four-factor model.

4.3.3.1 The EBF3 and Fama-French Five-factor Models

Table 4.5 shows the results of our market-behavioral-emotional factor model returns on the Fama-French five-factor model with and without momentum. We find our emotion-imbued behavioral factor model mostly explains the Fama-French five-factor model with and without momentum factor returns. However, this factor model cannot explain the PEAD and EMO factor premia.

In Panel A of Table 4.5 both Fama-French specifications account for the FIN factor premium, with alphas of about 0.20%, because of the presence of an operating profitability factor. Neither Fama-French five-factor model can explain the PEAD factor premium, with an alpha of 0.55% ($t = 4.28$). Augmenting the momentum factor yields similar results. The PEAD factor produces a significant abnormal return despite a large loading of 0.21 ($t = 6.78$) on the MOM factor.

In parallel, when we test whether the FF5 model can explain our market-behavioral-emotional factor model, we find it cannot account for the EMO factor premium. EMO earns a significant alpha of 0.44% with Newey-West t -statistic of 5.41 even in the presence of SMB despite us using size in constructing the emotion beta factor with consequently SMB and EMO moderately correlated. Likewise, the investment and momentum factors do not have significant loadings on EMO. This shows investor emotions capture something distinct from the FF5 model factors.

We also examine whether our EBF3 model can usefully explain the FF5 factors. Panel B of Table 4.5 shows that our EBF3 model largely subsumes the Fama-French five-factor model. In spanning regressions, most Fama-French factors earn insignificant abnormal returns. The SMB's EBF3 factor model alpha is insignificant ($\alpha = 0.14\%$ with $t = 0.86$) largely because the emotion beta factor is explaining the size factor premium ($\beta_{EMO} = 0.40$ with $t = 2.81$). Intuitively, this makes sense as small growth firms with largely subjective valuations dominate the EMO factor premium.⁷ Controlling for the EBF3 model the HML factor has an economically small and insignificant alpha of 0.05% ($t = 0.28$). Together the behavioral and emotion beta factors explain the returns earned by HML as the factor loadings are large and highly statistically significant.

In contrast, the RMW factor has an EBF3 alpha of 0.22% with t -statistic of 2.22, mainly because of the absence of a factor relating to profitability in the EBF3 model. PEAD does not contribute to explaining profitability and EMO has moderate explanatory power. Most of spanning regression power comes from the FIN factor which has a large and significant factor loading ($\beta_{FIN} = 0.43$ with $t = 8.46$). Both the CMA (investment) and momentum factors have insignificant EBF3 factor model alphas ($\alpha = 0.16\%$ and 0.11% with $t = 1.37$ and 0.48). FIN helps to explain CMA, whereas PEAD explains the momentum factor premium as FIN and PEAD exhibit high correlations with investment and momentum factors.

We also perform the Gibbons, Ross, and Shanken (1989, GRS) test on the null hypothesis that the alphas of the main EBF3 factors in the Fama-French five-factor regressions are jointly zero. Panel C shows that for the null that the alphas of the FIN, PEAD, and EMO factors are jointly zero with a GRS statistic of 18.31 (p -value = 0.00) in FF5, and 16.99 (p -value = 0.00) including the momentum factor. On the other hand, for the null that the alphas of SMB, HML, RMW, and CMA, with or without MOM factors, are jointly zero, the GRS statistic is 2.50 (p -value = 0.04), and 1.99 (p -value = 0.07) in EBF3. These GRS statistics are very low and only significant at the 5% and 10% levels respectively, compared to the GRS statistics in the Fama-French model.

⁷ The average book-to-market ratio of high emotion-based portfolio (SH and BH) is 0.81 compared to the average of 1.11 of low emotion-based portfolio (SL and BL). The difference in average book-to-market ratios is -0.30 with a Newey-West t -statistic of -10.02.

Taken together, the Fama-French five-factor model with or without momentum cannot explain the market-behavioral-emotional factor model premia. As such, the more parsimonious EBF3 factor model largely subsumes the Fama-French five-factor model.

4.3.3.2 The EBF3 and q -factor Model

Table 4.6 presents the factor spanning regression results of the emotion-imbued behavioral factor model and the q -factor model of Hou et al. (2015). The key factors in the q -factor model are size, investment-to-assets, and profitability. Our EBF3 model mostly explains the factor premia generated by the q -factor model.

In Panel A, we first test whether the q -factor model can explain the factor premia of our EBF3 model. The q -factor model fails to explain the returns earned by the PEAD and EMO factors. The PEAD q -factor alpha is 0.46% with t -statistic of 3.31. The q -factor model's investment-to-assets and profitability factors explain the PEAD factor without any success. The EMO factor records a q -factor model alpha of 0.48% with a t -statistic of 4.67. All the q -model factors, i.e., size, investment-to-assets, and profitability have significant factor loadings but still cannot carry the load of our EMO factor.

In Panel B, we explore whether our EBF3 factor model can explain q -factor model premia. The EMO factor ($\beta_{EMO} = 0.39$ with $t = 2.51$) fully captures the factor premium of size as SMB has only a EBF3 factor model alpha of 0.17% with t -statistic of 0.97. The FIN factor mostly captures the investment-to-assets factor with a significant factor loading ($\beta_{FIN} = 0.28$ and $t = 5.31$). Because of the absence of a profitability factor, our EBF3 factor model cannot explain the profitability factor premium.

Next, in Panel C, we examine the GRS statistics with the null hypothesis that all EBF3 factor alphas are jointly zero in the q -factor model. The GRS statistic is 18.87 (p -value = 0.00) which convincingly rejects the null hypothesis. When we test that all q -factor model alphas are jointly zero in the EBF3 factor model the GRS statistic comes down to only 3.09 (p -value = 0.03). Thus, we demonstrate that our EBF3 factor model does a comparatively better job in explaining the q -factor model.

4.3.3.3 The EBF3 and Barillas-Shanken Model

Table 4.7 presents the factor spanning regression results of the emotion-imbued behavioral factor model and the Barillas-Shanken model. Because their model includes the size (SMB), investment (IVA), and profitability (ROE) factors of the q -factor model and the Fama-French momentum (MOM) factor which we have already discussed in above subsections while comparing these two models, we only assess whether the BS6 model can explain the EBF3 model. In Panel A, we show that the 6-factor Barillas-Shanken model cannot explain the PEAD and EMO factors. PEAD has a BS6 model alpha of 0.45% ($t = 4.00$) despite value and momentum factors in their model having significant factor loadings. EMO has a BS6 model alpha of 0.51% ($t = 5.41$) though most of BS6 factors have significant loadings showing that EMO captures unique information content. The FIN factor, however, has an insignificant alpha of 0.21% as value, investment, and profitability share the load to explain it.

In Panel B, we test whether the EBF3 factor model can explain the Barillas-Shanken model's sixth factor, which is the value (HML^m) factor of Asness and Frazzini (2013). HML^m is constructed based on sequential sorts on size and then on book-to-market, where book equity is 6-months prior to the fiscal year end but the market equity is updated monthly. The EBF3 factor model fully explains the HML^m factor premium as both FIN and PEAD have significant factor loadings. In Panel C, we report the GRS statistics. First, for the null that the FIN, PEAD, and EMO factor alphas are jointly zero, the GRS statistic is large 20.79 (p -value = 0.00) in the Barillas-Shanken six-factor model. Alternatively, the GRS statistic is only 3.34 (p -value = 0.00). Taken together, we find that our emotion-imbued behavioral factor model performs better in explaining the factor premia of the Barillas-Shanken model.

4.3.3.4 The EBF3 and Mispricing Factor Model

Table 4.8 presents the factor spanning regression results of the emotion-imbued behavioral factor model and the mispricing factor model of Stambaugh-Yuan. The key mispricing factors are mainly constructed based on investment and profitability measures. The MGMT (management) factor contains net stock issues, composite issues, accruals, net operating assets, asset growth, and annual change in gross property, plant, and equipment plus the annual change in inventories scaled by lagged book assets. The PERF (performance) factor contains failure probability, O-score, momentum, gross profitability, and return on assets. Hou et al. (2019) point out how the construction of mispricing-factor model deviates for the traditional approach in at least three ways. First, its mispricing factors are constructed using the breakpoints of 20

and 80 percentiles as opposed to 30 and 70 percentiles (Fama and French, 1993, 2015; Hou et al., 2015). Second, the Stambaugh-Yuan uses CRSP breakpoints instead of NYSE breakpoints. Finally, its size factor contains stocks from the middle portfolios of the mispricing factors. These deviations make the mispricing factors more prone to the effect of microcaps and the extreme values used to construct the factors. Hou et al. (2019) show that this construction has significant impact on the model's performance.

In panel A, we use the Stambaugh-Yuan mispricing-factor model to explain returns generated by the factors of emotion-imbued behavioral factor model. The mispricing model cannot explain the factor premia earned by the PEAD and EMO factors. The PEAD factor has a mispricing model alpha of 0.28% with t -statistic of 2.28. Only the performance (PERF) factor records a positive and significant loading. The emotion beta factor has a large mispricing model alpha of 0.46% ($t = 4.41$). Size has a significant loading as we use NYSE market capitalization in constructing our EMO. The MGMT factor also has a significant negative loading, understandably so, because EMO is negatively correlated with it. The mispricing model captures the FIN factor premium as by construction both use net and composite stock issues, and CRSP breakpoints of 20 and 80 percentiles.

In Panel B, we use the EBF3 factor model to explain the mispricing factors. The size factor premium is fully explained by our emotion beta factor ($\beta_{EMO} = 0.40$ with $t = 2.94$) as we use the NYSE size median in construction. Both the management and performance mispricing factors survive despite FIN and EMO having significant positive loadings on MGMT factors ($\beta_{FIN} = 0.46$ with $t = 5.67$ and $\beta_{EMO} = -0.23$ with $t = -2.57$), and PEAD on the PERF factor ($\beta_{PERF} = 0.88$ with $t = 6.76$). These results, however, are susceptible to the mispricing factor model construction mechanisms.

Next, in Panel C, we present the GRS statistic for the null that the alphas of the FIN, PEAD, and EMO factors are jointly zero. This is 12.78 (p -value = 0.00). Alternatively, for the GRS test, the null hypothesis that the alphas of the SMB, MGMT, and PERF factors are jointly zero has a test statistic of 4.39 (p -value = 0.00). As such, the emotion-imbued behavioral factor model performs better in explaining the non-parsimonious mispricing factor model than the other way around.

4.3.3.5 The EBF3 and Other Prominent Factors

Panel A of Table 4.9 presents the spanning regressions of other prominent factors such as the

Pastor and Stambaugh (2003) liquidity (LIQ), and Frazzini and Pedersen (2014) betting against beta (BAB) factors on our emotion-imbued behavioral factor model. Both the LIQ and BAB factors earn economically significant factor premia of 0.48% ($t = 2.31$) and 0.81% ($t = 2.66$) respectively in our sample period. However, the LIQ and BAB factors have statistically insignificant EBF3 factor model alphas of 0.34% and 0.56% (with $t = 1.47$ and $t = 1.69$). The PEAD and EMO factors have insignificant factor loadings. The FIN factor pulls all the weight in explaining the BAB factor with a loading of 0.46 and t -statistic = 4.72. Thus, our model still performs better in explaining other prominent asset pricing factors.

In Panel B, we use a ‘kitchen sink’ regression of the EMO factor returns on all alternative model factors to provide further evidence that EMO is distinct. We demonstrate that EMO continues to earn a significant alpha of 0.51% per month ($t = 4.86$), even after controlling for the exposure to all other proposed factors in alternative models.

Overall, our emotion-augmented behavioral factor model largely explains factor premia generated by most of the factors of different models. We also confirm that EMO offers abnormally high returns relative to all the other factors we examine, including the investment, profitability, and mispricing factors.

4.4 EBF3 and Anomaly Returns

If our emotion-imbued behavioral factor model can account for many stock characteristics both in the short- and long-run, then EBF3 should be able to explain robust anomalies identified in the extant literature. Hou et al. (2015) and Daniel et al. (2020) show that their HXZ4 and BF3 models can explain many anomalies. Following their line of research, this section examines how well our emotion-imbued behavioral factor model explains market anomalies. We draw on the list of robust anomalies considered in Hou et al. (2015) that earn significant excess returns over their sample period of 1972 to 2012. We add two further anomalies to this list, the cash-based operating profitability (CbOP) of Ball et al. (2016) considered by Daniel et al. (2020), and the quality-minus-junk (QMJ) of Asness, Frazzini, and Pedersen (2019).

Following Daniel et al. (2020), we divide these anomalies in two groups, short- and long-horizon anomalies. In the short-horizon anomaly category, we have 12 anomalies – five related to earnings momentum (SUE-1, SUE-6, ABR-1, ABR-6, and RE-1), three related to price or return momentum (R6-6, R11-1, and I-MOM), and four based on short-term

profitability (ROEQ, ROAQ, NEI, and FP). In the long-horizon category, we cover 22 anomalies – three based on long-term profitability (GPA, CbOP, QMJ), five related to value (B/M, E/P, CF/P, NPY, and DUR), 10 based on investment and financing (IVA, IG, IvG, IvC, OA, NOA, POA, PTA, NSI, and CSI), and finally, four related to intangibles (OCA, AD/M, RDM, and OL). Table 4.10 describes the list of anomalies and provides the mean returns, t -statistics, and Sharpe ratios of their associated long/short (L-S) anomaly portfolios. Out of the 34 anomalies considered, we find only 10 economically significant anomalies across our sample period from 1995 to 2018.

To examine how well our emotion-imbuéd behavioral factor model accounts for these various return anomalies, we run anomaly portfolio regressions of the long-short (L-S) portfolio returns on the 4-factor model (EBF3) with MKT, FIN, PEAD, and EMO. If a model is efficient, the regression alphas of the L-S portfolios should not be statistically distinguishable from zero. We, then, run a horse race between competing models. Specifically, we compare the performance of our market-behavioral-emotional model with standard and recently proposed factor models, such as the CAPM, FF3, Carhart4, FF5, HXZ4, BS6, and SY4.

4.4.1 Explaining Short-horizon Anomalies

Table 4.11 summarizes the comparative performance of competing factor models in explaining the set of 34 anomalies. We separately compare model performance on the 12 short-horizon anomalies (Panel A), the 22 long-horizon anomalies (Panel B), and all 34 anomalies (Panel C). The column labelled ‘H-L ret’ reports the monthly average excess return of each Long-Short (L-S) anomaly portfolio. The other columns report the regression alphas of each L-S portfolio return for different factor models. At the foot of each panel, we summarize model performance using several statistics: (1) the number of significant alphas (α); (2) average absolute alphas ($|\alpha|$); (3) average absolute t -values of alphas ($|t|$); (4) F -statistics and p -values to test whether the average t^2 of alphas for a given model are larger than the average t^2 of our composite-model alphas; and (5) the GRS F -statistics and p -values to test the null hypothesis that all alphas are jointly zero (Gibbons et al., 1989).

Panel A of Table 4.11 compares how different models explain the 12 short-horizon anomalies. We look first at the number of significant alphas at the 5% level. Among standard factor models, the CAPM and FF3 models each cannot capture 11 anomalies. The Carhart4, FF5, and BS6 models do not explain three anomalies each. The HXZ4 misses two anomalies.

The mispricing model SY4 misses only one factor. Not surprisingly, the FF3 and FF5 models perform poorly, as these models are designed to price only longer-horizon anomalies. Combining the emotion factor with MKT, FIN, and PEAD, our emotion-imbued behavioral factor model fully captures all the 12 anomalies. Overall, the evidence suggests that the emotion-imbued behavioral factor augmented model is very successful in capturing the abnormal returns associated with earnings and return momentum.⁸

The EBF3 model produces an average absolute alpha ($|\alpha|$) of 0.23% and absolute t ($|t| = 0.96$) which are smaller than those for the CAPM, FF3, Carhart4, FF5, and SY4 models. Only the HXZ4 and BS6 models have lower average absolute alpha and t -statistic but fail to explain all the anomalies. BS6 also sacrifices parsimony as it is built on five characteristics. The F -tests suggest that the average of the squared t -statistics for the estimated alphas (t^2) under all other models are significantly larger than the average t^2 of EBF3 alphas except for the HXZ4, BS6, and SY4 models. However, these models have significant GRS statistics compared to our EBF3 model. EBF3 gives the smallest GRS F -statistic and does not reject the null hypothesis that all alphas are jointly zero (GRS $F = 0.91$, $p = 0.53$). Among the other models only the SY4 model performs better. However, the explanatory power of the mispricing model is largely dependent on its factor construction mechanism (Hou et al., 2019). All other models have substantially larger GRS F -statistics than the EBF3 model. Overall, we document that our composite emotion-imbued behavioral factor model outperforms other asset pricing models in capturing short-horizon anomalies.

4.4.2 Explaining Long-horizon Anomalies

To test the effectiveness of our EBF3 factor model in explaining long-horizon anomalies, Panel B of Table 4.11 compares how different models deal with the list of 22 long-horizon anomalies. We first consider the number of significant alphas. Among standard factor models, the CAPM, FF3, and Carhart4 models cannot capture more than half of the anomalies, the BS6 model has 7 significant alphas, and the HXZ4 and FF5 models cannot explain 6 and 5 anomalies respectively. The non-parsimonious SY4 mispricing factor model, constructed using a non-traditional approach and 11 characteristics, has only two significant alphas. Our EBF3 model (with MKT, FIN, PEAD, and EMO) has only three significant alphas outperforming all other

⁸ Our EMO factor alone can capture returns generated by 4 anomalies, i.e., SUE1, SUE6, ABR6, and R6-6, which is comparatively better than CAPM and FF3 models.

models except SY4.

Other statistics confirm the good performance of both the SY4 and EBF3 models. The EBF3 model has average absolute alpha ($|\alpha|$) of 0.26%, and absolute t ($|t|$) of 1.15% only second to the elaborate SY4 model. F -tests suggest that the average of the squared t -statistics for estimated alphas (t^2) under the CAPM, FF3, Carhart4, FF5, and BS6 models differ significantly to the average t^2 of EBF3 alphas. However, average t^2 s for the HXZ4 and SY4 models are not significantly different from the average t^2 of EBF3 alphas. Furthermore, the GRS F -tests reject the null for all models for our sample period. Our model's GRS F -statistic ($F = 1.94$) is only larger than that of SY4 which has the lowest GRS F -statistic ($F = 1.34$).

Overall, our composite market-behavioral-emotional factor model largely outperforms other prominent factor models. Our model is only second to the non-parsimonious mispricing factor model that employs 11 characteristics, more than any of the other factor models, and adopts a non-traditional approach in constructing its constituent factors. Our traditionally constructed EBF3 model does a similar job with many fewer characteristics.

4.4.3 All 34 Anomalies

Panel C of Table 4.11 summarizes model performance across all 34 anomalies. Our EBF3 and the SY4 model both cannot explain only three anomalies while the CAPM, FF3, Carhart4, BS6, FF5, and HXZ4 models have 25, 24, 14, 10, 8, and 8 significant alphas, respectively.^{9,10} Our market-behavioral-emotional factor model has average absolute alpha ($|\alpha|$) = 0.25%, absolute t ($|t|$) = 1.08%, and GRS F -statistic = 1.55 with overall performance only comparable to the SY4 model. However, the SY4 model is non-parsimonious, i.e., it uses 11 characteristics to construct a four-factor model whereas our model uses only three characteristics. The SY4 model is also sensitive to methods used for factor construction. Hou et al. (2019) find that once they construct the SY4 model using a traditional approach the performance is similar to the q -factor model of Hou et al. (2015). Moreover, factors built on the same characteristics as the

⁹ Overall, the BF3 model cannot explain four anomalies (unreported). The inclusion of EMO keeps the power of the BF3 model intact and adds incremental explanatory power in explaining the list of 34 anomalies.

¹⁰ The EMO further enhances the performance of BF3 as we consider anomalies that earn significant returns during our sample period. Out of the 10 significant anomalies, the EBF3 cannot explain three compared to four in BF3 model. The average absolute alpha and t -statistic goes down from 0.40 to 0.35 and from 1.79 to 1.55, respectively (unreported).

anomalies to be explained will perform better at explaining these anomalies for mechanical reasons (Daniel and Titman, 1997). From this perspective, our emotion-imbued behavioral factor model, in practice, performs better at capturing extant asset pricing anomalies.

Overall, our emotion-imbued behavioral factor model (EBF3) with a market factor, two behavioral factors, with an augmented emotion factor outperforms both traditional and recent prominent models in explaining robust anomalies. Our findings suggest that many of the existing anomalies, such as earnings and return momentum, profitability, value, investment and financing, and intangibles, can be attributed to systematic and behavior- and emotion-based mispricing.

4.4.4 Detailed Factor Regressions of Selected Anomalies

In this sub-section, we present detailed factor regression results for each anomaly. We show, for brevity, statistics only for the Long-Short (L-S) hedged anomaly portfolios. Table 4.12 reports alphas and factor loadings from time-series regressions of anomaly portfolio returns on different factor models. We investigate factor loadings to gain knowledge about the factors that explain different anomalies.

4.4.4.1 Earnings and Price Momentum

To examine how different models and factors perform, we start with exploring the earnings and price momentum. Our test assets cover five earnings momentum anomalies (SUE-1, SUE-6, ABR-1, ABR-6, and RE-1), and three price momentum anomalies (R6-6, R11-1, and I-MOM).

Panel A of Table 4.12 shows that, FF5 does not capture the ABR1 and ABR6 anomalies mainly because of the lack of a momentum (MOM) factor. Panels B and C show that the ROE factor of the HXZ4 model and the momentum factor (MOM) of the BS6 model help explain momentum related anomalies, except for SUE-6 and ABR-1. Similarly, panel D shows that the PERF factor, which is a composite factor formed on five anomaly variables including price momentum, explains most of these anomalies except SUE6. Notably, Panel E shows that the FIN factor, designed to capture long horizon anomalies, cannot explain earnings and momentum. However, PEAD and EMO successfully explain all anomalies.

Overall, the EMO factor, measuring the emotional utility stocks have for investors, in

conjunction with PEAD exhibit stronger pricing power for price and earnings momentum than does the MOM factor based on past returns, the ROE factor based on earnings profitability, the composite PERF factor based on momentum, distress, and profitability, and behavioral based FIN factors. These findings provide significant empirical evidence that integral investor emotions are powerful drivers of decision-making that need to be included in factor models to explain short-term anomalies.

4.4.4.2 Profitability

We also examine the performance of comparable factor models in explaining profitability-related anomalies. Our test assets include four short-horizon (ROEQ, ROAQ, NEI, and FP) and three long-horizon (GP/A, CbOP, and QMJ) profitability anomalies.

Panel A of Table 4.12 shows that even with a profitability factor, RMW, FF5 cannot explain three out five profitability anomalies. HXZ4, in Panel B, misses the CbOP and QMJ anomalies as the model's profitability-based ROE factor helps explain all other profitability anomalies including FP. In Panel C, BS6 cannot explain the premia earned by the FP, CbOP and QMJ anomaly portfolios as their profitability-based ROE factor helps explain the rest of the profitability anomalies. Despite the inclusion of profitability characteristics in the PERF factor the SY4 model fails to fully explain the premia generated by the CbOP and QMJ anomaly portfolios. Our EBF3 composite model, however, explains 5 out of the 7 anomalies despite having no profitability factor. Our emotion beta factor, EMO, performs exceptionally well in explaining short- and long-horizon profitability anomalies, with significant factor loadings.

Overall, despite not measuring profitability effect directly, the EMO factor captures the emotional utility investors derive from stocks by attaching emotional value to them and the PEAD factor designed to capture earnings surprises perform better in capturing the profitability anomalies. These two factors capture the profitability effects better than the profitability factors of FF5 and BS6.

4.4.4.3 Value

We further investigate value anomalies and the associated performance of different factor models. Our test assets include five value-growth anomalies (B/M, E/P, CF/P, NPY, and DUR).

Table 4.12 shows that all the FF5, HXZ4, BS6, SY4, and EBF3 models fully capture

value-based anomalies. Value factors, HML and HML^m, of FF5 and BS6 have significant factor loadings in explaining the value-growth anomalies as by construction they have very similar to the characteristics of value-growth anomalies. The investment factor, IVA, of HXZ4 and BS6 dominates other factors and explain the value premia. The IVA factor is constructed using investment-to-assets that captures value characteristics. The MGMT factor of SY4 includes value-related characteristics and fully explains value anomalies. In our EBF3 model, the FIN factor has most of the significant factor loadings. Its PEAD and emotion factor also contribute to explaining these anomalies.

4.4.4.4 Investment and Financing

We next examine anomalies related to investment and financing. Our test assets include 8 investment (IVA, IG, IvG, IvC, OA, NOA, POA, and PTA) and two financing anomalies (NSI and CSI).

Panel A Table 4.12 shows that the investment (CMA) factor of the FF5 helps explain all but two anomaly portfolios – inventory changes (IvC) and net operating accruals (NOA), as CMA is constructed using investment-to-assets. In panels B and C, the investment (IVA) factor of the HXZ4 and BS6 model explains all but three (OA, NOA, and NSI) anomaly portfolios. In panel D, the SY4 model fully explains all investment and financing anomalies because its MGMT factor is constructed using a combination of stock issues, accruals, and asset growth. Panel E reports that the FIN factor, designed to capture long-horizon anomalies using stock issuance characteristics, explains all but one (NOA) of the investment and financing anomalies.

Overall, our parsimonious EBF3 model has the ability to explain most of the investment and financing long-horizon anomalies using only three characteristics.

4.4.4.5 Intangibles

Finally, we investigate anomalies related to intangibles. Our test assets include four intangibles anomaly portfolios (OC/A, AD/M, RD/M, and OL).

Except for our emotion-imbued behavioral factor model and the mispricing model of Stambaugh-Yuan none of the other models are able to explain all intangible anomalies. In Panel A of Table 4.12, The FF5 model cannot explain RD/M as its investment factor, CMA, does not account for investment in research and development. Despite a large factor loading of the

RMW factor. The size (SMB) and profitability (RMW) factors of FF5 help explain the rest of the intangible anomalies. Similarly, the investment factor of HXZ4 cannot contribute to explain the RD/M anomaly (Panel B). It seems that the IVA factor misses important information relating to research and development expenditure that investors value. In Panel C, the BS6 model fails to explain the OC/A and RD/M anomalies. The two factors MGMT and PERF share the load in SY4 model. All the behavior and emotion factors play a role in the EBF3 model.

Overall, our results suggest that the emotion-imbued behavioral factor model can explain extant robust anomalies. Our EMO factor performs particularly well in pricing short-horizon earnings and return momentum, and profitability-based anomalies.

4.4.5 Detailed Results for Classic Anomalies

In this subsection, we present more detailed results for the classic anomalies to the Fama-French model, i.e., earnings and price momentum. We also present results for cash-based operating profitability (CbOP), which all the comparable models fail to capture.

4.4.5.1 Earnings Momentum (SUE-1) and Price Momentum (R11-1)

We first consider earnings momentum SUE-1. Panel A of Table 4.13 presents the factor regressions of SUE-1 deciles. Across these, the Fama-French five-factor model has five significant alphas. The HXZ4 and BS6 models have 9 significant alphas. The mispricing model of SY4 has 7 significant alphas. In contrast to these models, the emotion-imbued behavioral factor model has five significant alphas which is only comparable to the FF5 model.

We then examine the R11-1 deciles in Panel B. Across the R11-1 deciles, the FF5 model has 3 significant alphas. The HXZ4 and BS6 models have 5 and 7 significant alphas respectively. The mispricing model of SY4 has 7 significant alphas. In comparison, the emotion-imbued behavioral factor model has 3 significant alphas. Thus, the EBF3 factor model performs at least as well as the Fama-French five-factor model and better than other models in explaining earnings and price momentum.

4.4.5.2 Cash-based Operating Profitability (CbOP)

We now examine the cash-based operating profitability anomaly, which remains robust, with no model able to explain its anomaly returns. Ball et al. (2016) document that firms with high

cash-based operating profitability earn higher average returns than firms with low cash-based operating profitability.

Table 4.14 shows why the emotion-imbued behavioral factor model fails to explain the CbOP anomaly. The high CbOP decile has a large positive emotion beta factor loading of 0.25 with $t = 2.53$. More importantly, the PEAD factor loading is -0.15 for the low decile and 0.17 for the high decile. Both the emotion and PEAD factors perform poorly in explaining this long-term anomaly. The FIN factor has large loadings for both the extreme deciles; however, this is not sufficient to explain the CbOP anomaly returns. Since both emotion and PEAD capture short-term anomalies with better precision they fail to do the same in the case of CbOP.

4.5 Conclusion

We show empirically investor integral emotions are priced. In particular, we enhance the powerful behavioral factor model of Daniel et al. (2020) by adding a distinct emotion factor to capture the commonality in mispricing associated with investor emotions together with risk and behavioral psychological biases. Our emotion factor is motivated by the emotion in decision-making and object relations theory in psychology. We test the ability of our emotion-imbued behavioral factor model to explain well-known return anomalies. Our composite approach blends risk, cognitive biases, and investor emotions.

We find that our market-behavioral-emotional factor model captures a large set of the anomalies examined by Hou et al. (2015) and performs at least as well as, and in most cases better than extant factor models. In particular, we compare our model's performance with the CAPM (Sharpe 1964), the 3- and 5-factor model of Fama and French (1993, 2015), the momentum-based model of Carhart (1997), the q -factor model of Hou et al. (2015), the model of Barillas and Shanken (2018), and the mispricing model of Stambaugh and Yuan (2017).

Our endeavor contributes to the literature on factor pricing models and anomalies. Our composite behavioral-emotional factor model has attractive psychology-based motivation and demonstrates empirically that behavioral biases and important investor integral emotions such as excitement and anxiety capture different dimensions of investor psychology. Our main contribution is to suggest that we need to recognize the important role played by investor emotion in asset pricing more formally.

Figure 4. 1: Emotion-imbued Choice Model

The figure shows how integral and incidental emotions enter into the decision-making process. Lerner, Li, Valdesolo, and Kassam (2015) show how emotions influence decision making and their impact is outside the scope of rational choice models.

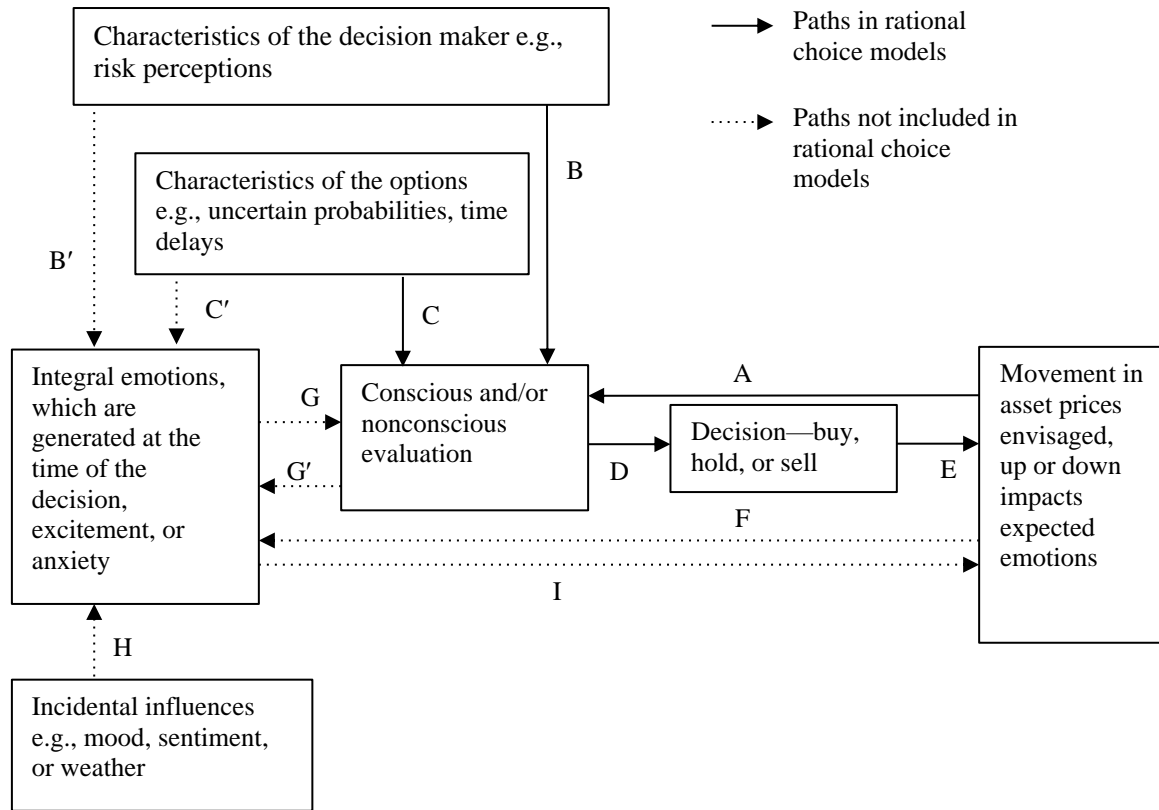


Table 4. 1: Summary Statistics of Factor Portfolios

The table reports the mean and standard deviations of monthly factor returns for a set of traded factors. In addition, we report the t -statistic testing whether the mean return is different from zero, the corresponding monthly Sharpe ratio, and the sample period for each return factor. These factors include the MKT, SMB, HML, and MOM factors proposed by Fama and French (1993) and Carhart (1997) and modified versions of these factors proposed by Hou, Xue, and Zhang (2015, HXZ4), Stambaugh and Yuan (2017, SY4), and Asness and Frazzini (2013). We additionally include the profitability factors RMW, and ROE of Fama and French (2015), and Hou, Xue, and Zhang (2015); the investment factors CMA and IVA of Fama and French (2015) and Hou, Xue, and Zhang (2015); the two mispricing factors MGMT and PERF of Stambaugh and Yuan (2017); the short- and long- horizon behavioral factors PEAD and FIN of Daniel, Hirshleifer, and Sun (2020); the betting against beta (BAB) factor of Frazzini and Pedersen (2014); and the liquidity (LIQ) factor of Pastor and Stambaugh (2003). Monthly factor returns are either from Kenneth French's Web page or provided by corresponding authors in their respective websites or from AQR website. EMO is the emotion factor. The estimation period is from January 1995 to December 2018.

| | Mean | SD | t -statistics | SR | N | Sample period |
|------------------|------|------|-----------------|------|-----|-----------------|
| MKT | 0.66 | 4.35 | 2.35 | 0.15 | 287 | 1995:02-2018:12 |
| SMB | 0.16 | 3.16 | 0.95 | 0.05 | 287 | 1995-02:2018-12 |
| SMB (HXZ4) | 0.24 | 3.27 | 1.34 | 0.07 | 287 | 1995:02-2018:12 |
| SMB (SY4) | 0.35 | 2.86 | 2.11 | 0.12 | 263 | 1995:02-2016:12 |
| HML | 0.16 | 3.08 | 0.73 | 0.05 | 287 | 1995-02:2018-12 |
| HML ^m | 0.08 | 3.88 | 0.33 | 0.02 | 287 | 1995-02:2018-12 |
| MOM | 0.44 | 5.02 | 1.43 | 0.09 | 287 | 1995-02:2018-12 |
| RMW | 0.34 | 2.79 | 1.77 | 0.12 | 287 | 1995-02:2018-12 |
| CMA | 0.22 | 2.13 | 1.60 | 0.10 | 287 | 1995-02:2018-12 |
| IVA (HXZ4) | 0.20 | 2.08 | 1.56 | 0.10 | 287 | 1995-02:2018-12 |
| ROE (HXZ4) | 0.39 | 2.84 | 2.32 | 0.14 | 287 | 1995-02:2018-12 |
| MGMT | 0.53 | 3.08 | 2.67 | 0.17 | 263 | 1995-02:2016-12 |
| PERF | 0.73 | 4.73 | 2.31 | 0.15 | 263 | 1995-02:2016-12 |
| FIN | 0.52 | 4.51 | 1.80 | 0.12 | 287 | 1995-02:2018-12 |
| PEAD | 0.45 | 2.13 | 3.61 | 0.21 | 287 | 1995-02:2018-12 |
| BAB | 0.81 | 4.03 | 2.66 | 0.20 | 287 | 1995-02:2018-12 |
| LIQ | 0.48 | 3.60 | 2.31 | 0.13 | 287 | 1995-02:2018-12 |
| EMO | 0.39 | 2.03 | 3.34 | 0.19 | 287 | 1995-02:2018-12 |

Table 4. 2: Correlations

The table reports Pearson correlations between factor portfolio returns. The factor definitions are available in the caption of Table 4.1.

| Variables | MKT | SMB | SMB (HXZ4) | SMB (SY4) | HML | HML ^m | MOM | RMW | CMA | IVA (HXZ4) | ROE (HXZ4) | MGMT | PERF | FIN | PEAD | BAB | LIQ | EMO |
|------------------|-------------|-------------|---------------|--------------|-------------|------------------|-------------|-------------|-------------|---------------|---------------|-------------|-------------|-------------|------|-------|------|-----|
| MKT | 1 | | | | | | | | | | | | | | | | | |
| SMB | 0.21 | 1 | | | | | | | | | | | | | | | | |
| SMB (HXZ4) | 0.23 | 0.97 | 1 | | | | | | | | | | | | | | | |
| SMB (SY4) | 0.19 | 0.94 | 0.94 | 1 | | | | | | | | | | | | | | |
| HML | -0.15 | -0.11 | -0.05 | -0.06 | 1 | | | | | | | | | | | | | |
| HML ^m | 0.08 | -0.04 | -0.05 | -0.05 | 0.72 | 1 | | | | | | | | | | | | |
| MOM | -0.27 | 0.03 | 0.08 | 0.09 | -0.21 | -0.73 | 1 | | | | | | | | | | | |
| RMW | -0.48 | -0.49 | -0.47 | -0.41 | 0.43 | 0.18 | 0.08 | 1 | | | | | | | | | | |
| CMA | -0.35 | -0.04 | 0.00 | 0.00 | 0.65 | 0.43 | 0.01 | 0.30 | 1 | | | | | | | | | |
| IVA (HXZ4) | -0.31 | -0.13 | -0.10 | -0.11 | 0.67 | 0.48 | -0.03 | 0.36 | 0.92 | 1 | | | | | | | | |
| ROE (HXZ4) | -0.49 | -0.45 | -0.37 | -0.34 | 0.18 | -0.27 | 0.48 | 0.74 | 0.19 | 0.22 | 1 | | | | | | | |
| MGMT | -0.45 | -0.31 | -0.26 | -0.23 | 0.66 | 0.37 | 0.08 | 0.55 | 0.74 | 0.76 | 0.41 | 1 | | | | | | |
| PERF | -0.50 | -0.15 | -0.13 | -0.10 | -0.19 | -0.58 | 0.75 | 0.42 | 0.10 | 0.03 | 0.67 | 0.18 | 1 | | | | | |
| FIN | -0.53 | -0.46 | -0.42 | -0.37 | 0.64 | 0.36 | 0.05 | 0.81 | 0.58 | 0.66 | 0.60 | 0.81 | 0.28 | 1 | | | | |
| PEAD | -0.14 | 0.06 | 0.07 | 0.07 | -0.27 | -0.52 | 0.53 | -0.10 | -0.10 | -0.17 | 0.19 | -0.06 | 0.45 | -0.11 | 1 | | | |
| BAB | -0.34 | -0.17 | -0.12 | -0.09 | 0.41 | 0.09 | 0.26 | 0.56 | 0.35 | 0.40 | 0.52 | 0.41 | 0.31 | 0.57 | 0.04 | 1 | | |
| LIQ | 0.18 | 0.12 | 0.11 | 0.12 | -0.09 | -0.02 | 0.04 | -0.09 | -0.12 | -0.12 | -0.12 | -0.25 | 0.05 | -0.17 | 0.08 | 0.05 | 1 | |
| EMO | 0.45 | 0.45 | 0.42 | 0.41 | -0.54 | -0.30 | -0.06 | -0.66 | -0.45 | -0.51 | -0.55 | -0.67 | -0.22 | -0.74 | 0.09 | -0.45 | 0.14 | 1 |

Table 4. 3: Ex Post Tangency Portfolios

The table reports summary statistics for the ex post tangency portfolios for various factor-portfolio combinations. The asterisk after factors SMB and HML indicates that these factors have modified versions, and the asterisk after models FF5, HXZ4, BS6, and SY4 indicates these models use modified factors. The factor definitions are available in the caption of Table 4.1. The estimation period is from January 1995 to December 2018.

| | Portfolio weights | | | | | | | | | | | | | Tangency portfolios | | |
|--------------------------|-------------------|------|-------|-------|------|-------|------|------|------|------|-------|-------|-------------|---------------------|------|-------------|
| | MKT | SMB* | HML* | MOM | RMW | CMA | IVA | ROE | MGMT | PERF | PEAD | FIN | EMO | Mean | SD | SR |
| (1) FF3 | 0.55 | 0.09 | 0.36 | | | | | | | | | | | 0.44 | 2.54 | 0.17 |
| (2) Carhart4 | 0.40 | 0.01 | 0.31 | 0.27 | | | | | | | | | | 0.44 | 1.88 | 0.23 |
| (3) FF5* | 0.27 | 0.14 | -0.21 | | 0.42 | 0.38 | | | | | | | | 0.39 | 1.12 | 0.34 |
| (4) HXZ4* | 0.26 | 0.13 | | | | | 0.23 | 0.38 | | | | | | 0.39 | 1.16 | 0.32 |
| (5) BS6* | 0.23 | 0.12 | 0.10 | 0.07 | | | 0.13 | 0.34 | | | | | | 0.37 | 1.06 | 0.34 |
| (6) SY4* | 0.30 | 0.15 | | | | | | | 0.34 | 0.21 | | | | 0.59 | 1.33 | 0.43 |
| (7) BF2 | | | | | | | | | | | 0.77 | 0.23 | | 0.46 | 1.84 | 0.24 |
| (8) BF3 | 0.29 | | | | | | | | | | 0.46 | 0.25 | | 0.53 | 1.32 | 0.39 |
| (9) EMO+MKT | 0.27 | | | | | | | | | | | | 0.73 | 0.46 | 2.26 | 0.20 |
| (10) EBF2 | | | | | | | | | | | 0.21 | 0.31 | 0.48 | 0.44 | 1.02 | 0.42 |
| (11) EBF3 | 0.12 | | | | | | | | | | 0.20 | 0.25 | 0.43 | 0.47 | 0.85 | 0.53 |
| (12) EBF3+MOM | 0.12 | | | 0.03 | | | | | | | 0.18 | 0.30 | 0.37 | 0.47 | 0.93 | 0.49 |
| (13) EBF3+RMW+CMA | 0.11 | | | | 0.20 | 0.18 | | | | | -0.09 | 0.20 | 0.40 | 0.43 | 0.90 | 0.45 |
| (14) EBF3+IVA+ROE | 0.10 | | | | | | 0.12 | 0.22 | | | -0.01 | 0.18 | 0.40 | 0.42 | 0.86 | 0.47 |
| (15) EBF3+MGMT+PERF | 0.13 | | | | | | | | 0.19 | 0.12 | 0.02 | 0.16 | 0.38 | 0.52 | 0.95 | 0.53 |
| (16) All factors ex. EMO | 0.25 | 0.14 | -0.09 | -0.14 | 0.04 | -0.13 | 0.10 | 0.09 | 0.35 | 0.17 | 0.24 | -0.02 | | 0.56 | 1.09 | 0.50 |
| (17) All factors | 0.10 | 0.04 | 0.01 | -0.08 | 0.05 | -0.14 | 0.10 | 0.09 | 0.26 | 0.09 | 0.11 | -0.01 | 0.38 | 0.48 | 0.70 | 0.66 |

Table 4. 4: EMO Factor versus the BF3 Model

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. In Panel A, we estimate spanning regression of our EMO factor on the behavioral 3-factor model of Daniel et al. (2020, BF3). EMO is our investor emotion factor. MKT, FIN, and PEAD, are the factors of BF3 factor model. MKT, FIN, and PEAD are market, financing, and post-earnings announcement drift factors. In Panel B, we estimate spanning regression of factors of the BF3 model on EMO, and EMO and MKT factors. Newey-West corrected t -statistics (with six lags) are shown in parentheses. The estimation period is from January 1995 to December 2018.

| Panel A: Explaining the EMO factor | | | | | Panel B: Explaining the BF3 factors | | | | | |
|------------------------------------|-------------------|-------------------|----------------------|----------------|-------------------------------------|------|-------------------|---------------------|----------------------|---------------------|
| | α | MKT | FIN | PEAD | Adj. R ² | | α | MKT | EMO | Adj. R ² |
| EMO | 0.25** [2.26] | 0.21*** [5.80] | | | 20.34 | MKT | 0.28 [1.06] | | 0.97*** [5.57] | 20.34 |
| | 0.56*** [6.51] | | -0.33*** [-16.34] | | 54.34 | FIN | 1.16*** [5.05] | | -1.64*** [-11.53] | 54.34 |
| | 0.35*** [3.22] | | | 0.08 [0.71] | 0.45 | PEAD | 0.41*** [3.68] | | 0.09 [0.74] | 0.45 |
| | 0.56*** [6.05] | | -0.33*** [-16.57] | 0.01 [0.23] | 54.19 | FIN | 1.23*** [5.75] | -0.25*** [-3.74] | -1.39*** [-8.75] | 58.80 |
| | 0.51*** [5.03] | 0.04* [1.73] | -0.31*** [-12.22] | 0.03 [0.58] | 54.71 | PEAD | 0.44*** [4.04] | -0.11*** [-3.13] | 0.19* [1.70] | 4.00 |
| | | | | | | | | | | |

Table 4. 5: Spanning Tests: The EBF3 Model versus the Fama-French Five- and Six-Factor Models

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. In Panel A, we estimate spanning regression of factors of the emotion-imbuend behavioral factor model (EBF3) on the 5-factor model of Fama and French (2015, FF5). FIN, PEAD, and EMO are the factors of emotion-imbuend behavioral factor model. SMB, HML, RMW, CMA, and MOM are Fama-French size, value, operating profitability, investment, and momentum factors. In Panel B, we estimate spanning regression of factors of the FF5 on EBF3 model. Newey-West corrected t -statistics (with six lags) are shown in parentheses. In Panel C, we estimate the GRS statistic following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Explaining EBF3 factor model | | | | | | | | | Panel B: Explaining FF5 and FF6 factor models | | | | | | |
|--|----------|----------|----------|--|----------|---------|---------|--|---|----------|---------|--|----------|----------|------------|
| | α | MKT | SMB | HML | RMW | CMA | MOM | Adj. R^2 | | α | MKT | FIN | PEAD | EMO | Adj. R^2 |
| FIN | 0.21* | -0.15*** | -0.21*** | 0.35*** | 0.82*** | 0.47*** | | 82.89 | SMB | 0.14 | -0.04 | -0.21* | 0.00 | 0.40*** | 22.74 |
| | (1.80) | (-5.31) | (-4.70) | (5.97) | (11.05) | (6.30) | | | | (0.86) | (-0.55) | (-1.69) | (0.01) | (2.81) | |
| | 0.20 | -0.14*** | -0.21*** | 0.37*** | 0.81*** | 0.46*** | 0.02 | 82.89 | HML | 0.05 | 0.16** | 0.41*** | -0.22*** | -0.28*** | 48.52 |
| | (1.65) | (-5.35) | (-4.77) | (6.77) | (11.57) | (6.40) | (0.85) | | | (0.28) | (2.33) | (6.63) | (-3.77) | (-3.60) | |
| PEAD | 0.55*** | -0.10*** | 0.03 | -0.20*** | -0.04 | 0.04 | | 20.32 | RMW | 0.22** | -0.04 | 0.43*** | -0.03 | -0.16* | 66.42 |
| | (4.28) | (-2.80) | (0.62) | (-3.75) | (-0.55) | (0.45) | | | | (2.22) | (-1.00) | (8.46) | (-0.53) | (-1.84) | |
| | 0.44*** | -0.04 | -0.01 | -0.07 | -0.10* | -0.03 | 0.21*** | 30.18 | CMA | 0.16 | -0.03 | 0.24*** | -0.05 | -0.04 | 33.26 |
| | (4.20) | (-1.16) | (-0.21) | (-1.30) | (-1.68) | (-0.38) | (6.78) | | | (1.37) | (-0.64) | (3.21) | (-0.82) | (-0.41) | |
| EMO | 0.44*** | 0.09*** | 0.15*** | -0.20*** | -0.22*** | -0.09 | | 58.31 | MOM | 0.11 | -0.24** | -0.03 | 1.18*** | -0.07 | 31.13 |
| | (5.41) | (3.25) | (4.21) | (-5.31) | (-5.88) | (-1.37) | | | | (0.48) | (-2.34) | (-0.20) | (5.56) | (-0.29) | |
| | 0.45*** | 0.08*** | 0.15*** | -0.21*** | -0.22*** | -0.09 | -0.03 | 58.49 | | | | | | | |
| | (5.42) | (2.88) | (4.38) | (-5.02) | (-5.52) | (-1.15) | (-1.20) | | | | | | | | |
| Panel C: GRS statistics | | | | | | | | | | | | | | | |
| $\alpha_{FIN}, \alpha_{PEAD}, \alpha_{EMO} = 0$ in FF5 | | | | $\alpha_{FIN}, \alpha_{PEAD}, \alpha_{EMO} = 0$ in FF6 | | | | $\alpha_{SMB}, \alpha_{HML}, \alpha_{RMW}, \alpha_{CMA} = 0$ in EBF3 | | | | $\alpha_{SMB}, \alpha_{HML}, \alpha_{RMW}, \alpha_{CMA}, \alpha_{MOM} = 0$ in EBF3 | | | |
| GRS | | | | 18.31 | | | | GRS | | | | 1.99 | | | |
| p | | | | 0.00 | | | | p | | | | 0.07 | | | |

Table 4. 6: Spanning Tests: The EBF3 Model versus the q -factor Model

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. In Panel A, we estimate spanning regression of factors of the emotion-imbued behavioral factor model (EBF3) on the q -factor model of Hou, Xue, and Zhang (2015, HXZ4). FIN, PEAD, and EMO are the factors of emotion-imbued behavioral factor model. SMB, IVA, and ROE are HXZ4 size, investment, and profitability factors. In Panel B, we estimate spanning regression of factors of the HXZ4 on EBF3 model. Newey-West corrected t -statistics (with six lags) are shown in parentheses. In Panel C, we estimate the GRS statistic following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Explaining EBF3 factor model | | | | | | | Panel B: Explaining q -factor factor model | | | | | | |
|---|-------------------|---------------------|---------------------|---------------------|---------------------|---------------------|--|-------------------|--------------------|-------------------|--------------------|---------------------|---------------------|
| | α | MKT (HXZ4) | SMB (HXZ4) | IVA (HXZ4) | ROE (HXZ4) | Adj. R ² | | α | MKT | FIN | PEAD | EMO | Adj. R ² |
| FIN | 0.26 (1.58) | -0.16*** (-3.01) | -0.30*** (-3.05) | 1.12*** (9.03) | 0.52*** (5.06) | 70.72 | SMB (HXZ4) | 0.17 (0.97) | -0.01 (-0.10) | -0.18 (-1.30) | 0.04 (0.27) | 0.39** (2.51) | 19.38 |
| PEAD | 0.46*** (3.31) | -0.07 (-1.63) | 0.11 (1.44) | -0.26*** (-3.12) | 0.17** (2.21) | 10.61 | IVA (HXZ4) | 0.11 (1.08) | 0.01 (0.37) | 0.28*** (5.31) | -0.09** (-2.05) | -0.06 (-0.82) | 43.66 |
| EMO | 0.48*** (4.67) | 0.06** (2.20) | 0.15*** (3.79) | -0.37*** (-8.11) | -0.22*** (-6.84) | 52.36 | ROE (HXZ4) | 0.33*** (2.94) | -0.11** (-2.05) | 0.24*** (3.63) | 0.30*** (3.10) | -0.31*** (-2.61) | 46.28 |
| Panel C: GRS statistics | | | | | | | | | | | | | |
| $\alpha_{\text{FIN}}, \alpha_{\text{PEAD}}, \alpha_{\text{EMO}} = 0$ in q -factor | | | | | | | $\alpha_{\text{SMB (HXZ4)}}, \alpha_{\text{IVA (HXZ4)}}, \alpha_{\text{ROE (HXZ4)}} = 0$ in EBF3 | | | | | | |
| GRS | | 18.87 | | | | | GRS | | 3.09 | | | | |
| p | | 0.00 | | | | | p | | 0.03 | | | | |

Table 4. 7: Spanning Tests: The EBF3 Model versus the Barillas and Shanken Factor Model

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. In Panel A, we estimate spanning regression of factors of the emotion-imbued behavioral factor model (EBF3) on the 6-factor model of Barillas and Shanken (2018, BS6). FIN, PEAD, and EMO are the factors of emotion-imbued behavioral factor model. SMB, IVA, and ROE are HXZ4 size, investment, and profitability factors; HML^m is the Asness and Frazzini (2013) value factor; and MOM is the Fama-French momentum factor. In Panel B, we estimate spanning regression of only HML^m factor on EBF3 model as in Table 4.5 and 4.6 we already test the rest of the factors. Newey-West corrected t -statistics (with six lags) are shown in parentheses. In Panel C, we estimate the GRS statistic following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Explaining EBF3 factor model | | | | | | | | | Panel B: Explaining BS factor model | | | | | | |
|--|-------------------|---------------------|---------------------|---------------------|-------------------|---------------------|--------------------|---------------------|---|----------------|-------------------|-------------------|---------------------|------------------|---------------------|
| | α | MKT | SMB | HML ^m | IVA (HXZ4) | ROE (HXZ4) | MOM | Adj. R ² | | α | MKT | FIN | PEAD | EMO | Adj. R ² |
| FIN | 0.21 (1.48) | -0.20*** (-5.36) | -0.26*** (-4.43) | 0.56*** (8.81) | 0.55*** (5.68) | 0.67*** (7.48) | 0.14*** (3.17) | 78.45 | HML ^m | 0.18 (0.87) | 0.24*** (2.67) | 0.34*** (4.07) | -0.79*** (-5.59) | -0.17 (-1.11) | 41.18 |
| PEAD | 0.45*** (4.00) | -0.03 (-0.85) | 0.01 (0.29) | -0.14** (-2.38) | -0.04 (-0.45) | -0.05 (-0.76) | 0.15*** (3.29) | 31.15 | | | | | | | |
| EMO | 0.51*** (5.41) | 0.08*** (3.11) | 0.14*** (4.11) | -0.26*** (-5.94) | -0.11* (-1.69) | -0.28*** (-6.76) | -0.08** (-2.53) | 59.67 | | | | | | | |
| Panel C: GRS statistics | | | | | | | | | | | | | | | |
| $\alpha_{\text{FIN}}, \alpha_{\text{PEAD}}, \alpha_{\text{EMO}} = 0$ in BS | | | | | | | | | $\alpha_{\text{SMB}}, \alpha_{\text{HML}^m}, \alpha_{\text{IVA (HXZ)}}, \alpha_{\text{ROE (HXZ)}}, \alpha_{\text{MOM}} = 0$ in EBF3 | | | | | | |
| GRS | | 20.79 | | | | | | | GRS | | 3.34 | | | | |
| p | | 0.00 | | | | | | | p | | 0.01 | | | | |

Table 4. 8: Spanning Tests: The EBF3 Model versus the Mispricing Factor Model

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. In Panel A, we estimate spanning regression of factors of the emotion-imbued factor behavioral model (EBF3) on the mispricing factor model of Stambaugh and Yuan (2017, SY4). FIN, PEAD, and EMO are the factors of emotion-imbued behavioral factor model. SMB, MGMT, and PERF are SY4 size, management, and performance related factors. In Panel B, we estimate spanning regression of factors of the SY4 on EBF3 model. Newey-West corrected t -statistics (with six lags) are shown in parentheses. In Panel C, we estimate the GRS statistic following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Explaining EBF3 factor model | | | | | | | Panel B: Explaining SY4 factor model | | | | | | |
|--|-------------------|---------------------|-------------------|---------------------|-------------------|------------|---|------------------|---------------------|-------------------|-------------------|--------------------|------------|
| | α | MKT (SY4) | SMB (SY4) | MGMT | PERF | Adj. R^2 | | α | MKT | FIN | PEAD | EMO | Adj. R^2 |
| FIN | 0.23 (1.61) | -0.19*** (-3.86) | -0.29* (-1.76) | 1.03*** (13.78) | 0.05 (0.76) | 72.01 | SMB (SY4) | 0.26* (1.69) | -0.02 (-0.33) | -0.11 (-1.02) | 0.03 (0.29) | 0.40*** (2.94) | 16.53 |
| PEAD | 0.28** (2.28) | 0.02 (0.43) | 0.07 (0.97) | -0.08 (-1.40) | 0.23*** (6.01) | 21.65 | MGMT | 0.33** (2.29) | 0.00 (0.08) | 0.46*** (5.67) | 0.04 (0.71) | -0.23** (-2.57) | 65.98 |
| EMO | 0.46*** (4.41) | 0.08*** (3.97) | 0.18*** (2.78) | -0.37*** (-9.93) | -0.01 (-0.34) | 53.63 | PERF | 0.52** (2.44) | -0.40*** (-4.46) | 0.13 (1.06) | 0.88*** (6.76) | 0.03 (0.21) | 38.99 |
| Panel C: GRS statistics | | | | | | | | | | | | | |
| $\alpha_{FIN}, \alpha_{PEAD}, \alpha_{EMO} = 0$ in SY4 | | | | | | | $\alpha_{SMB(SY4)}, \alpha_{MGMT}, \alpha_{PERF} = 0$ in EBF3 | | | | | | |
| GRS | 12.78 | | | | | | GRS | 4.39 | | | | | |
| p | 0.00 | | | | | | p | 0.00 | | | | | |

Table 4. 9: Spanning Tests: Additional Factors and the ‘Kitchen Sink’ Model

This table reports the results of spanning regressions where α is the intercept and Adj. R^2 is the goodness-of-fit in percent. We estimate spanning regression of Pastor and Stambaugh liquidity (LIQ) and Frazzini and Pedersen betting against beta (BAB) factors on the emotion-imbued behavioral factor model (EBF3). FIN, PEAD, and EMO are the factors of emotion-imbued behavioral factor model. In ‘kitchen sink’ model we include all factors from Carhart4, FF5, HXZ4, BS6, SY4, and behavioral factors of Daniel et al. (2020). Newey-West corrected t -statistics (with six lags) are shown in parentheses. In Panel C, we estimate the GRS statistic following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Explaining LIQ and BAB factors by EBF3 model | | | | | | | | | | | | | | | | | | |
|---|-------------------|-------------------|-------------------|---------------------|------------------|------------------|----------------|------------------|-------------------|-------------------|----------------|------------------|-----------------|------------------|------------------|---------------------|------------------|---------------------|
| | α | | | | MKT | | | | FIN | | | | PEAD | | | | EMO | Adj. R ² |
| LIQ | 0.34 (1.47) | | | | 0.13 (1.60) | | | | -0.05 (-0.57) | | | | 0.15 (1.28) | | | | 0.04 (0.18) | 3.35 |
| BAB | 0.56* (1.69) | | | | -0.02 (-0.27) | | | | 0.46*** (4.72) | | | | 0.19* (1.69) | | | | -0.15 (-0.78) | 32.63 |
| Panel B: The kitchen sink model | | | | | | | | | | | | | | | | | | |
| | α | MKT | SMB | HML | MOM | RMW | CMA | IVA | ROE | MGMT | PERF | FIN | PEAD | LIQ | BAB | Adj. R ² | | |
| EMO | 0.51*** (4.86) | 0.07*** (2.75) | 0.11*** (2.78) | -0.15*** (-3.74) | 0.01 (0.27) | -0.06 (-0.95) | 0.13 (0.86) | -0.14 (-1.31) | -0.14* (-1.90) | -0.15* (-1.93) | 0.01 (0.38) | -0.04 (-0.61) | 0.01 (0.17) | -0.02 (-0.60) | -0.00 (-0.04) | 62.14 | | |

Table 4. 10: List of Anomalies

The table lists the anomalies that we study closely matching the set of robust anomalies considered in Hou, Xue, d Zhang (2015). The anomalies are grouped into six categories: (i) earnings momentum; (ii) price or return momentum; (iii) profitability; (iv) value; (v) investment and financing; and (vi) intangibles. The table also presents Long-Short portfolio average excess returns (in percentage) and Sharpe ratios. Monthly factor returns are collected from the respective authors and AQR websites. Newey-West corrected *t*-statistics (with six lags) are shown in parentheses. The estimation period is from January 1995 to December 2018.

| Category | Symbol | List of anomalies | L-S ret (%) | SR | Category | Symbol | List of anomalies | L-S ret (%) | SR |
|-------------------|--------|--|-------------------|------|--------------------------|--------|--|-------------------|------|
| Earnings momentum | SUE-1 | Standardized unexpected earnings (1-month holding period), Foster, Olsen, and Shevlin (1984) | 0.29 (1.63) | 0.08 | Value | B/M | Book-to-market equity, Rosenberg, Reid, and Lanstein (1985) | 0.12 (0.39) | 0.03 |
| | SUE-6 | Standardized unexpected earnings (6-month holding period), Foster, Olsen, and Shevlin (1984) | 0.04 (0.34) | 0.01 | | E/P | Earnings-to-price, Basu (1983) | 0.13 (0.41) | 0.03 |
| | ABR-1 | Cumulative abnormal returns around earnings announcements (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996) | 0.48** (2.51) | 0.13 | | CF/P | Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994) | 0.03 (0.08) | 0.00 |
| | ABR-6 | Cumulative abnormal returns around earnings announcements (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996) | 0.33** (2.07) | 0.13 | Investment and financing | IVA | Investment-to-assets, Lyandres, Sun, and Zhang (2008) | 0.29 (1.18) | 0.07 |
| Return momentum | RE-1 | Revisions in analysts' earnings forecasts (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996) | 0.59* (1.91) | 0.10 | | IG | Investment growth, Xing (2008) | 0.40* (1.80) | 0.12 |
| | R6-6 | Return momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993) | 0.58 (1.40) | 0.09 | | IvG | Inventory growth, Belo and Lin (2012) | 0.13 (0.69) | 0.04 |
| | R11-1 | Return momentum (11-month prior returns, 1-month holding period), Fama and French (1996) | 0.78 (1.60) | 0.09 | | IvC | Inventory changes, Thomas and Zhang (2002) | 0.34* (1.87) | 0.10 |
| Profitability | I-MOM | Industry momentum (6-month prior returns, 6-month holding period), Moskowitz and Grinblatt (1999) | 0.51* (1.70) | 0.09 | | OA | Operating accruals, Sloan (1996) and Hribar and Collins (2002) | 0.23 (1.16) | 0.07 |
| | ROEQ | Quarterly ROE (1-month holding period), Haugen and Baker (1996) | 0.52 (1.41) | 0.09 | | NOA | Net operating assets, Hirshleifer et al. (2004) | 0.89*** (4.17) | 0.25 |
| | ROAQ | Quarterly ROA (1-month holding period), Balakrishnan, Bartov, and Faurel (2010) | 0.46 (1.38) | 0.09 | | POA | Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011) | 0.41* (1.95) | 0.13 |
| | NEI | Number of consecutive quarters with earnings increases (1-month holding period), Barth, Elliott, and Finn (1999) | 0.33** (2.22) | 0.12 | | PTA | Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011) | 0.24 (1.28) | 0.07 |
| | FP | Failure probability (quarterly updated, 6-month holding period), Campbell, Hilscher, and Szilagyi (2008) | 0.80* (1.68) | 0.10 | | NSI | Net share issuance, Pontiff and Woodgate (2008) | 0.58** (2.43) | 0.16 |
| | GP/A | Gross profits-to-assets ratio, Novy-Marx (2013) | 0.40** (2.28) | 0.13 | | CSI | Composite share issuance, Daniel and Titman (2006) | 0.47* (1.79) | 0.11 |
| | CbOP | Cash-based operating profitability, Ball et al. (2016) | 0.82*** (3.22) | 0.20 | Intangibles | OC/A | Organizational capital-to-assets, Eisfeldt and Papanikolaou (2013) | 0.69** (2.29) | 0.14 |
| | QMJ | Quality-minus-Junk, Aness, Frazzini, and Pedersen (2019) | 0.84*** (2.79) | 0.18 | | AD/M | Advertisement expense-to-market, Chan, Lakonishok, and Sougiannis (2001) | 0.34 (0.99) | 0.06 |
| Value | NPY | Net payout yield, Boudoukh et al. (2007) | 0.51* (1.71) | 0.12 | | RD/M | R&D-to-market, Chan, Lakonishok, and Sougiannis (2001) | 1.01*** (3.04) | 0.18 |
| | DUR | Equity duration, Dechow, Sloan, and Soliman (2004) | 0.04 (0.14) | 0.00 | | OL | Operating leverage, Novy-Marx (2011) | 0.44* (1.89) | 0.11 |

Table 4. 11: Comparative Model Performance

This table reports comparative performance of different factor models in explaining anomalies. We compare three sets of factor models. The first set includes standard factor models: the CAPM, Fama-French 3-factor model (FF3), and Carhart 4-factor model (Carhart4). The second set includes four recent models: the 5-factor model of Fama and French (2015, FF5), the q -factor model of Hou, Xue, and Zhang (2016, HXZ4), the 6-factor model of Barillas and Shanken (2018), and the 4-factor mispricing model of Stambaugh and Yuan (2017, SY4). The last set includes our emotion-imbued behavioral factor model: a 4-factor market-behavioral-and-emotional composite model (EBF3) with MKT, FIN, PEAD, and EMO. The table reports the regression alphas from time-series regressions of Long-Short anomaly portfolio returns on each factor model, with Newey-West corrected t -statistics (six lags). Panel A compares model performance for short-horizon anomalies, Panel B for long-horizon anomalies, and Panel C for all anomalies. As comparative statistics, we summarize the number of significant alphas at 5% level, the average absolute alphas and t -values, the F -statistics and p -values that test whether the average t^2 of alphas under a given model is significantly larger than the average t^2 of the composite-model alphas, and the GRS F -statistics and p -values following Gibbons, Ross, and Shanken (1989). The estimation period is from January 1995 to December 2018.

| Panel A: Short-horizon anomalies | | | | | | | | | | | |
|----------------------------------|--|--------|---------|---------|---------|----------|---------|---------|---------|---------|-------|
| Category | List of anomalies | Symbol | H-L ret | CAPM | FF3 | Carhart4 | FF5 | HXZ4 | BS6 | SY4 | EBF3 |
| Earnings momentum | Standardized unexpected earnings | SUE-1 | 0.29 | 0.43*** | 0.45*** | 0.18 | 0.19 | -0.05 | -0.05 | -0.07 | 0.15 |
| | | SUE-6 | 0.04 | 0.14 | 0.17 | -0.05 | -0.02 | -0.25** | -0.27** | -0.27** | 0.05 |
| | CAR around earnings announcements | ABR-1 | 0.48** | 0.54*** | 0.58*** | 0.36* | 0.63*** | 0.45** | 0.43** | 0.22 | -0.03 |
| | | ABR-6 | 0.33** | 0.32** | 0.37** | 0.18 | 0.42*** | 0.27 | 0.25* | 0.11 | 0.04 |
| | Revisions in analysts' earnings forecasts | RE-1 | 0.59* | 0.88*** | 0.91*** | 0.40* | 0.64* | 0.12 | 0.07 | 0.22 | 0.59* |
| Return momentum | Past returns | R6-6 | 0.58 | 0.76** | 0.88** | 0.02 | 0.72* | 0.12 | 0.00 | -0.41 | 0.17 |
| | | R11-1 | 0.78 | 1.10*** | 1.23*** | 0.06 | 0.90* | 0.12 | -0.03 | -0.75 | 0.18 |
| Profitability | Industry momentum | I-MOM | 0.51* | 0.66** | 0.72** | 0.04 | 0.51 | 0.11 | 0.01 | -0.36 | 0.00 |
| | Quarterly ROE | ROEQ | 0.52 | 1.00*** | 0.95*** | 0.76*** | 0.22 | 0.04 | 0.03 | 0.12 | 0.42* |
| | Quarterly ROA | ROAQ | 0.46 | 0.88*** | 0.88*** | 0.65*** | 0.26 | 0.04 | 0.03 | 0.07 | 0.32 |
| | N. of consecutive quarters with earnings increases | NEI | 0.33** | 0.39*** | 0.44*** | 0.29* | 0.25* | 0.14 | 0.14 | 0.14 | 0.27 |
| Short-horizon anomalies | Failure probability | FP | 0.80* | 1.45*** | 1.56*** | 0.82*** | 1.00*** | 0.49 | 0.42** | -0.10 | 0.49* |
| | N. significant at α 5% | | 3 | 11 | 11 | 3 | 3 | 2 | 3 | 1 | 0 |
| | Average $ \alpha $ | | 0.48 | 0.71 | 0.76 | 0.32 | 0.48 | 0.18 | 0.14 | 0.24 | 0.23 |
| | Average $ t $ | | 1.65 | 2.72 | 3.02 | 1.52 | 1.78 | 0.85 | 0.88 | 0.85 | 0.96 |
| | F.-stat = Average t^2 /Average t^2 EBF3 | | 2.99** | 8.10*** | 9.93*** | 2.51* | 3.44** | 0.79 | 0.84 | 0.80 | |
| | p -value | | 0.05 | 0.00 | 0.00 | 0.07 | 0.04 | 0.29 | 0.27 | 0.29 | |
| | GRS F.-stat | | | 2.79*** | 3.51*** | 2.88*** | 2.12*** | 2.11*** | 2.16*** | 1.80** | 0.91 |
| | p -value | | | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.04 | 0.53 |

Table 4. 11: Continued

| Panel B: Long-horizon anomalies | | | | | | | | | | | |
|---------------------------------|---|--------|---------|---------|---------|----------|---------|---------|---------|---------|---------|
| Category | List of anomalies | Symbol | H-L ret | CAPM | FF3 | Carhart4 | FF5 | HXZ4 | BS6 | SY4 | EBF3 |
| Profitability | Gross profits-to-assets | GP/A | 0.40** | 0.42** | 0.42** | 0.35* | 0.10 | 0.15 | 0.16 | -0.07 | -0.01 |
| | Cash-based operating profitability | CbOP | 0.82*** | 1.04*** | 1.18*** | 1.07*** | 0.89*** | 0.98*** | 1.01*** | 0.70*** | 0.66*** |
| | Quality-minus-Junk | QMJ | 0.84*** | 1.24*** | 1.31*** | 1.15*** | 0.80*** | 0.85*** | 0.87*** | 0.53** | 0.75*** |
| Value | Book-to-market equity | B/M | 0.12 | 0.17 | -0.09 | -0.03 | -0.15 | -0.03 | -0.13 | -0.04 | 0.15 |
| | Earnings-to-price | E/P | 0.13 | 0.30 | 0.06 | 0.03 | -0.18 | -0.22 | -0.32 | 0.02 | 0.00 |
| | Cash flow-to-price | CF/P | 0.03 | 0.09 | -0.18 | -0.10 | -0.31 | -0.24 | -0.35 | 0.04 | -0.07 |
| | Net payout yield | NPY | 0.51* | 0.79*** | 0.67*** | 0.62*** | 0.25 | 0.32* | 0.28 | 0.24 | 0.23 |
| | Equity duration | DUR | 0.04 | -0.12 | 0.08 | 0.09 | 0.24 | 0.32 | 0.42* | 0.18 | 0.05 |
| | Investment-to-assets | IVA | 0.29 | 0.44* | 0.29 | 0.25 | 0.09 | 0.01 | 0.01 | -0.02 | 0.25 |
| | Investment growth | IG | 0.40* | 0.51** | 0.41** | 0.37* | 0.26 | 0.18 | 0.18 | 0.18 | 0.33 |
| | Inventory growth | IvG | 0.13 | 0.20 | 0.14 | 0.13 | -0.05 | -0.01 | -0.01 | -0.02 | 0.01 |
| | Inventory changes | IvC | 0.34* | 0.37** | 0.34* | 0.30 | 0.37** | 0.33* | 0.33* | 0.28 | 0.13 |
| | Operating accruals | OA | 0.23 | 0.15 | 0.21 | 0.22 | 0.37* | 0.46** | 0.45** | 0.35 | 0.17 |
| | Net operating accruals | NOA | 0.89*** | 0.82*** | 0.90*** | 0.73*** | 0.91*** | 0.83*** | 0.84*** | 0.28 | 0.53** |
| | Percent operating accruals | POA | 0.41* | 0.49** | 0.41** | 0.39** | 0.21 | 0.27 | 0.25 | 0.20 | 0.35* |
| | Percent total accruals | PTA | 0.24 | 0.42** | 0.35** | 0.34** | 0.10 | 0.17 | 0.17 | 0.11 | 0.22 |
| | Net share issuance | NSI | 0.58** | 0.80*** | 0.74*** | 0.67*** | 0.34* | 0.40** | 0.39** | 0.15 | 0.16 |
| | Composite share issuance | CSI | 0.47* | 0.76*** | 0.65*** | 0.59*** | 0.22 | 0.28 | 0.24 | 0.19 | 0.11 |
| | Organizational capital-to-assets | OC/A | 0.69** | 0.97*** | 0.93*** | 0.79*** | 0.47 | 0.46* | 0.50** | -0.01 | 0.36 |
| | Advertisement expense-to-market | AD/M | 0.34 | 0.29 | 0.35 | 0.21 | -0.27 | -0.15 | -0.19 | 0.06 | 0.26 |
| | R&D-to-market | RD/M | 1.01*** | 0.71** | 0.70** | 0.69** | 0.93*** | 0.93*** | 0.95*** | 0.30 | 0.67* |
| | Operating leverage | OL | 0.44* | 0.65*** | 0.61*** | 0.48** | 0.21 | 0.11 | 0.12 | 0.05 | 0.17 |
| Long-horizon anomalies | N. significant at α 5% | | 7 | 14 | 13 | 11 | 5 | 6 | 7 | 2 | 3 |
| | Average $ \alpha $ | | 0.41 | 0.53 | 0.50 | 0.44 | 0.35 | 0.35 | 0.37 | 0.18 | 0.26 |
| | Average $ t $ | | 1.71 | 2.25 | 2.33 | 2.10 | 1.68 | 1.56 | 1.76 | 0.85 | 1.15 |
| | F.-stat = Average t^2 /Average t^2 EBF3 | | 2.19* | 3.80** | 4.09** | 3.30** | 2.11* | 1.83 | 2.34* | 0.54 | |
| | p -value | | 0.09 | 0.03 | 0.03 | 0.04 | 0.09 | 0.12 | 0.08 | 0.41 | |
| | GRS F.-stat | | | 3.19*** | 3.55*** | 3.18*** | 2.37*** | 2.48*** | 2.80*** | 1.34 | 1.94*** |
| | p -value | | | 0.0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.41 | 0.01 |

Table 4. 11: Continued

| Panel C: All anomalies | | | | | | | | | | |
|---|--------|---------|---------|---------|----------|---------|---------|---------|-------|--------|
| | Symbol | H-L ret | CAPM | FF3 | Carhart4 | FF5 | HXZ4 | BS6 | SY4 | EBF3 |
| N. significant at α 5% | | 10 | 25 | 24 | 14 | 8 | 8 | 10 | 3 | 3 |
| Average $ \alpha $ | | 0.44 | 0.60 | 0.59 | 0.39 | 0.40 | 0.29 | 0.29 | 0.20 | 0.25 |
| Average $ t $ | | 1.69 | 2.42 | 2.57 | 1.89 | 1.71 | 1.31 | 1.45 | 0.85 | 1.08 |
| F.-stat = Average t^2 /Average t^2 EBF3 | | 2.42* | 4.97** | 5.63*** | 3.04** | 2.49* | 1.46 | 1.79 | 0.62 | |
| p -value | | 0.08 | 0.02 | 0.01 | 0.05 | 0.07 | 0.16 | 0.12 | 0.37 | |
| GRS F.-stat | | | 2.52*** | 2.81*** | 2.59*** | 2.07*** | 2.39*** | 2.69*** | 1.41* | 1.55** |
| p -value | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.07 | 0.03 |

Table 4. 12: Factor Regressions of Long-Short Anomaly Portfolios

This table reports alphas and factor betas from time-series regressions of Long-Short anomaly portfolio returns on recent prominent factor models. Panels A, B, C, and D report regression alphas and factor betas under the 5-factor model of Fama and French (2015), the q -factor model of Hou, Xue, and Zhang (2015), the 6-factor model of Barillas and Shanken (2018), and the 4-factor mispricing model of Stambaugh and Yuan (2017), respectively. Panel E reports the alphas and betas under our emotion-imbuend behavioral factor model (EBF3). Newey-West corrected t -statistics (with six lags) are shown in parentheses. The estimation period is from January 1995 to December 2018.

| | Earnings momentum | | | | Return momentum | | | | Profitability | | | | Value | | | | |
|--|-------------------|----------|----------|----------|-----------------|----------|----------|---------|---------------|----------|----------|----------|---------|----------|----------|----------|---------|
| | SUE-1 | SUE-6 | ABR-1 | ABR-6 | RE-1 | R6-6 | R11-1 | I-MOM | ROEQ | ROAQ | NEI | FP | GP/A | CbOP | QMJ | B/M | E/P |
| Panel A: 5-factor model of Fama and French (2015, FF5) | | | | | | | | | | | | | | | | | |
| α | 0.19 | -0.02 | 0.63*** | 0.42*** | 0.64* | 0.72* | 0.90* | 0.51 | 0.22 | 0.26 | 0.25* | 1.00*** | 0.10 | 0.89*** | 0.80*** | -0.15 | -0.18 |
| β_{MKT} | -0.08 | -0.04 | -0.14** | -0.04 | -0.23* | -0.25* | -0.39** | -0.18 | -0.21*** | -0.22*** | 0.00 | -0.62*** | 0.11** | -0.14** | -0.29*** | -0.01 | -0.04 |
| β_{SMB} | -0.01 | -0.07 | -0.00 | 0.07 | -0.35** | 0.12 | 0.15 | 0.27 | -0.38*** | -0.35*** | -0.01 | -0.55** | 0.17** | -0.51*** | -0.33*** | 0.46*** | 0.25*** |
| β_{HML} | -0.22** | -0.20** | -0.17 | -0.16** | -0.22 | -0.71*** | -0.91*** | -0.54** | -0.10 | -0.20*** | -0.22*** | -0.70*** | -0.20* | -0.62*** | -0.46*** | 0.87*** | 0.88*** |
| β_{RMW} | 0.45*** | 0.37*** | -0.10 | -0.00 | 0.50*** | 0.26 | 0.43 | 0.34 | 1.35*** | 1.22*** | 0.48*** | 0.97*** | 0.62*** | 0.56*** | 0.98*** | -0.10 | 0.48*** |
| β_{CMA} | 0.16 | 0.04 | -0.00 | -0.20 | 0.09 | 0.15 | 0.48 | 0.22 | 0.31** | 0.07 | -0.18 | 0.38 | 0.06 | 0.07 | 0.12 | 0.43** | 0.01 |
| Panel B: q -factor model of Hou, Xue, and Zhang (2015, HXZ4) | | | | | | | | | | | | | | | | | |
| α | -0.05 | -0.25** | 0.45** | 0.27 | 0.12 | 0.12 | 0.12 | 0.11 | 0.04 | 0.04 | 0.14 | 0.49 | 0.15 | 0.98*** | 0.85*** | -0.03 | -0.22 |
| β_{MKT} | 0.00 | 0.05* | -0.07 | 0.02 | -0.00 | -0.03 | -0.11 | -0.05 | -0.14*** | -0.12*** | 0.05 | -0.42*** | 0.07 | -0.18** | -0.33*** | -0.06 | -0.01 |
| β_{SMB} | 0.10 | 0.04 | 0.12 | 0.13* | -0.09 | 0.48* | 0.64** | 0.51** | -0.37*** | -0.30*** | -0.00 | -0.23 | 0.13** | -0.51*** | -0.38*** | 0.34*** | 0.14 |
| β_{IVA} | -0.03 | -0.11 | -0.33*** | -0.39*** | -0.04 | -0.67** | -0.64 | -0.44 | 0.49*** | 0.12 | -0.26*** | -0.32 | -0.06 | -0.51*** | -0.19** | 1.24*** | 1.01*** |
| β_{ROE} | 0.79*** | 0.70*** | 0.30*** | 0.26*** | 1.28*** | 1.30*** | 1.81*** | 1.02*** | 1.41*** | 1.40*** | 0.55*** | 1.79*** | 0.46*** | 0.46*** | 0.83*** | -0.39*** | 0.30** |
| Panel C: Barillas and Shanken (2018, BS6) | | | | | | | | | | | | | | | | | |
| α | -0.05 | -0.27** | 0.43** | 0.25* | 0.07 | 0.00 | -0.03 | 0.01 | 0.03 | 0.03 | 0.14 | 0.42** | 0.16 | 1.01*** | 0.87*** | -0.13 | -0.32 |
| β_{MKT} | 0.03 | 0.07*** | -0.03 | 0.06* | 0.06 | 0.11** | 0.08* | 0.06 | -0.16*** | -0.13*** | 0.06 | -0.33*** | 0.07 | -0.16** | -0.32*** | -0.10** | -0.06 |
| β_{SMB} | 0.02 | -0.04 | -0.01 | 0.01 | -0.31*** | -0.04 | -0.04 | 0.11 | -0.30*** | -0.28*** | -0.04 | -0.57*** | 0.15** | -0.54*** | -0.38*** | 0.35*** | 0.18** |
| β_{IVA} | 0.16 | -0.02 | -0.12 | -0.21*** | 0.13 | -0.15 | -0.00 | -0.12 | 0.23** | -0.02 | -0.19* | 0.04 | -0.08 | -0.14 | 0.00 | 0.35** | 0.06 |
| β_{ROE} | 0.59*** | 0.53*** | -0.00 | -0.02 | 0.79*** | 0.15 | 0.29** | 0.14 | 1.58*** | 1.47*** | 0.45*** | 1.04*** | 0.51*** | 0.34*** | 0.79*** | -0.25*** | 0.51*** |
| β_{MOM} | 0.14* | 0.15*** | 0.25*** | 0.23*** | 0.50*** | 1.10*** | 1.49*** | 0.90*** | -0.05 | 0.00 | 0.08 | 0.71*** | -0.05 | -0.09 | -0.08 | 0.39*** | 0.34*** |
| β_{HML}^m | -0.12 | -0.03 | -0.10 | -0.08 | 0.03 | -0.07 | -0.03 | 0.04 | 0.22** | 0.13 | -0.03 | -0.07 | 0.00 | -0.37*** | -0.20* | 0.96*** | 0.99*** |
| Panel D: 4-factor mispricing model of Stambaugh and Yuan (2017, SY4) | | | | | | | | | | | | | | | | | |
| α | -0.07 | -0.27** | 0.22 | 0.11 | 0.22 | -0.41 | -0.75 | -0.36 | 0.12 | 0.07 | 0.14 | -0.10 | -0.07 | 0.70*** | 0.53** | -0.04 | 0.02 |
| β_{MKT} | 0.03 | 0.06 | 0.01 | 0.07 | -0.03 | 0.20* | 0.25** | 0.17* | -0.20*** | -0.15** | 0.06 | -0.19 | 0.11* | -0.06 | -0.20*** | -0.04 | -0.09 |
| β_{SMB} | -0.06 | -0.11 | 0.04 | 0.07 | -0.43** | 0.27 | 0.38* | 0.35** | -0.65*** | -0.57*** | -0.13 | -0.55*** | 0.10* | -0.64*** | -0.51*** | 0.56*** | 0.17 |
| β_{MGMT} | 0.17** | 0.13** | -0.10 | -0.17** | 0.05 | -0.07 | 0.19 | -0.03 | 0.72*** | 0.48*** | 0.00 | 0.57*** | 0.26*** | -0.04 | 0.40*** | 0.68*** | 0.68*** |
| β_{PERF} | 0.41*** | 0.33*** | 0.30*** | 0.22*** | 0.64*** | 1.04*** | 1.43*** | 0.88*** | 0.48*** | 0.56*** | 0.28*** | 1.13*** | 0.18*** | 0.41*** | 0.47*** | -0.24*** | -0.08 |
| Panel E: 4-factor emotion-imbuend behavioral factor model (EBF3) | | | | | | | | | | | | | | | | | |
| α | 0.15 | 0.05 | -0.03 | 0.04 | 0.59* | 0.17 | 0.18 | 0.00 | 0.42* | 0.32 | 0.27 | 0.49* | -0.01 | 0.66*** | 0.75*** | 0.15 | 0.00 |
| β_{MKT} | -0.08 | -0.03 | 0.01 | 0.04 | -0.18 | -0.16 | -0.27* | -0.12 | -0.22*** | -0.22** | 0.01 | -0.50*** | 0.06 | -0.22** | -0.31*** | 0.07 | 0.07 |
| β_{FIN} | 0.09 | 0.02 | -0.05 | -0.08 | 0.03 | -0.12 | -0.01 | 0.00 | 0.68*** | 0.54*** | 0.01 | 0.48*** | 0.32*** | 0.22** | 0.40*** | 0.25** | 0.54*** |
| β_{PEAD} | 0.54*** | 0.36*** | 1.36*** | 0.74*** | 0.91*** | 1.54*** | 2.06*** | 1.37*** | 0.24* | 0.41*** | 0.40*** | 1.40*** | 0.11 | 0.31** | 0.42*** | -0.33** | -0.27** |
| β_{EMO} | -0.29 | -0.41*** | -0.21 | -0.06 | -0.79*** | -0.31 | -0.39 | -0.07 | -0.56*** | -0.47** | -0.31** | -0.61** | 0.40*** | 0.11 | -0.29** | -0.15 | -0.18 |

Table 4. 12: Continued

| | Value | | | Investment and financing | | | | | | | | | | Intangibles | | | |
|--|---------|----------|----------|--------------------------|---------|---------|----------|----------|----------|---------|----------|----------|----------|-------------|---------|----------|---------|
| | CF/P | NPY | DUR | IVA | IG | IvG | IvC | OA | NOA | POA | PTA | NSI | CSI | OC/A | AD/M | RD/M | OL |
| Panel A: 5-factor model of Fama and French (2015, FF5) | | | | | | | | | | | | | | | | | |
| α | -0.31 | 0.25 | 0.24 | 0.09 | 0.26 | -0.05 | 0.37** | 0.37* | 0.91*** | 0.21 | 0.10 | 0.34* | 0.22 | 0.47 | -0.27 | 0.93*** | 0.21 |
| β_{MKT} | 0.06 | -0.07 | 0.07 | -0.04 | -0.06 | 0.05 | -0.02 | 0.02 | 0.09 | 0.04 | -0.03 | -0.04 | -0.12*** | -0.17** | 0.28*** | 0.24*** | -0.09 |
| β_{SMB} | 0.25*** | -0.39*** | -0.07 | -0.13 | 0.08 | -0.14* | -0.21*** | -0.13 | -0.15 | -0.07 | -0.34*** | -0.23*** | -0.17* | 0.15 | 0.50*** | 0.49*** | 0.15* |
| β_{HML} | 1.01*** | 0.27*** | -0.83*** | 0.21*** | 0.13 | -0.04 | -0.02 | -0.08 | -0.40*** | 0.09 | 0.04 | 0.01 | 0.15** | -0.35 | 0.83*** | -0.07 | -0.06 |
| β_{RMW} | 0.21 | 0.56*** | -0.37*** | -0.20** | -0.05 | 0.02 | -0.38*** | -0.24* | -0.18 | 0.16* | 0.18* | 0.59*** | 0.63*** | 0.61*** | 0.55*** | -0.64*** | 0.77*** |
| β_{CMA} | 0.11 | 0.60*** | 0.09 | 1.24*** | 0.74*** | 0.79*** | 0.67*** | -0.20 | 0.32 | 0.54*** | 0.69*** | 0.48*** | 0.53*** | 0.72*** | 0.16 | 0.32 | 0.10 |
| Panel B: q -factor model of Hou, Xue, and Zhang (2015, HXZ4) | | | | | | | | | | | | | | | | | |
| α | -0.24 | 0.32* | 0.32 | 0.01 | 0.18 | -0.01 | 0.33* | 0.46** | 0.83*** | 0.27 | 0.17 | 0.40** | 0.28 | 0.46* | -0.15 | 0.93*** | 0.11 |
| β_{MKT} | 0.06 | -0.09 | 0.01 | -0.02 | -0.04 | 0.02 | -0.01 | 0.00 | 0.10 | 0.01 | -0.07 | -0.07 | -0.15*** | -0.23*** | 0.23** | 0.18** | -0.07 |
| β_{SMB} | 0.10 | -0.43*** | -0.01 | 0.02 | 0.15* | -0.12** | -0.10 | -0.18** | 0.01 | -0.07 | -0.34*** | -0.28*** | -0.23** | 0.23** | 0.31 | 0.65*** | 0.14* |
| β_{IVA} | 1.23*** | 1.08*** | -0.83*** | 1.45*** | 0.97*** | 0.81*** | 0.63*** | -0.25** | -0.16 | 0.69*** | 0.86*** | 0.66*** | 0.91*** | 0.47*** | 1.43*** | -0.08 | 0.25** |
| β_{ROE} | -0.11 | 0.34*** | -0.30** | -0.02 | 0.03 | -0.03 | -0.21 | -0.35*** | 0.09 | 0.02 | 0.05 | 0.40*** | 0.38*** | 0.57*** | -0.05 | -0.45** | 0.75*** |
| Panel C: Barillas and Shanken (2018, BS6) | | | | | | | | | | | | | | | | | |
| α | -0.35 | 0.28 | 0.42* | 0.01 | 0.18 | -0.01 | 0.33* | 0.45** | 0.84*** | 0.25 | 0.17 | 0.39** | 0.24 | 0.50** | -0.19 | 0.95*** | 0.12 |
| β_{MKT} | -0.01 | -0.12* | 0.06 | -0.02 | -0.04 | 0.02 | 0.01 | 0.02 | 0.14** | 0.00 | -0.07 | -0.08 | -0.17*** | -0.22*** | 0.15* | 0.21*** | -0.08 |
| β_{SMB} | 0.17* | -0.41*** | -0.06 | 0.01 | 0.14* | -0.12** | -0.16** | -0.24*** | -0.12 | -0.08 | -0.34*** | -0.26*** | -0.21** | 0.22** | 0.47*** | 0.60*** | 0.17* |
| β_{IVA} | 0.16 | 0.69*** | 0.12 | 1.43*** | 0.98*** | 0.81*** | 0.83*** | -0.16 | 0.26 | 0.56*** | 0.80*** | 0.54*** | 0.56*** | 0.77*** | 0.64** | 0.18 | 0.22* |
| β_{ROE} | 0.18 | 0.45*** | -0.53*** | -0.04 | 0.03 | -0.04 | -0.37*** | -0.49*** | -0.23 | 0.03 | 0.06 | 0.45*** | 0.46*** | 0.53*** | 0.41** | -0.59** | 0.81*** |
| β_{MOM} | 0.32*** | 0.11 | -0.31*** | 0.03 | 0.00 | 0.02 | 0.07 | 0.12 | 0.14 | 0.08 | 0.01 | 0.02 | 0.12** | -0.14 | -0.06 | 0.01 | -0.06 |
| β_{HML}^m | 1.08*** | 0.39*** | -0.97*** | 0.03 | -0.01 | 0.01 | -0.15 | -0.04 | -0.33** | 0.15 | 0.06 | 0.12 | 0.36*** | -0.33* | 0.70*** | -0.23 | 0.01 |
| Panel D: 4-factor mispricing model of Stambaugh and Yuan (2017, SY4) | | | | | | | | | | | | | | | | | |
| α | 0.04 | 0.24 | 0.18 | -0.02 | 0.18 | -0.02 | 0.28 | 0.35 | 0.28 | 0.20 | 0.11 | 0.15 | 0.19 | -0.01 | 0.06 | 0.30 | 0.05 |
| β_{MKT} | -0.06 | -0.08 | 0.07 | 0.00 | -0.05 | -0.00 | 0.01 | 0.02 | 0.32*** | -0.04 | -0.08 | -0.02 | -0.17*** | -0.08 | 0.08 | 0.44*** | -0.06 |
| β_{SMB} | 0.21 | -0.43*** | -0.04 | 0.09 | 0.22** | -0.05 | -0.01 | -0.11 | 0.03 | -0.02 | -0.32*** | -0.26** | -0.23 | 0.20* | 0.43* | 0.74*** | 0.00 |
| β_{MGMT} | 0.61*** | 0.93*** | -0.56*** | 0.85*** | 0.56*** | 0.44*** | 0.31*** | -0.25*** | 0.21** | 0.38*** | 0.58*** | 0.70*** | 0.78*** | 0.82*** | 0.79*** | 0.14 | 0.39*** |
| β_{PERF} | -0.28** | 0.04 | 0.02 | -0.07 | -0.06 | -0.07 | -0.08 | -0.03 | 0.29*** | -0.06 | -0.08 | 0.12*** | 0.06 | 0.24*** | -0.38** | 0.03 | 0.28*** |
| Panel E: 4-factor emotion-imbued behavioral factor model (EBF3) | | | | | | | | | | | | | | | | | |
| α | -0.07 | 0.23 | 0.05 | 0.25 | 0.33 | 0.01 | 0.13 | 0.17 | 0.53** | 0.35* | 0.22 | 0.16 | 0.11 | 0.36 | 0.26 | 0.67* | 0.17 |
| β_{MKT} | 0.17* | 0.05 | -0.02 | 0.01 | -0.03 | 0.02 | -0.02 | 0.01 | 0.11* | 0.01 | -0.02 | 0.02 | -0.03 | -0.17** | 0.36*** | 0.25** | -0.08 |
| β_{FIN} | 0.46*** | 0.70*** | -0.47*** | 0.31** | 0.26*** | 0.26*** | 0.16* | -0.13 | 0.01 | 0.22** | 0.34*** | 0.65*** | 0.72*** | 0.49*** | 0.53*** | -0.21 | 0.42*** |
| β_{PEAD} | -0.38** | 0.10 | 0.39*** | -0.00 | -0.09 | -0.11 | 0.05 | 0.11 | 0.48*** | -0.08 | -0.09 | 0.11 | 0.08 | 0.27* | -0.77** | 0.18 | 0.20* |
| β_{EMO} | -0.18 | -0.41*** | 0.19 | -0.31 | -0.02 | 0.04 | 0.29 | 0.18 | 0.17 | -0.07 | -0.27 | 0.03 | -0.08 | 0.18 | -0.22 | 0.53** | 0.03 |

Table 4. 13: Earnings Momentum (SUE-1) and Price Momentum (R11-1) Deciles

The table reports two classic anomalies to Fama-French factors – standardized unexpected earnings (SUE-1) and past return (R11-1). M , α_{FF5} , α_{HXZ4} , α_{BS6} , α_{SY4} , and α_{EBF3} are the average excess return, the Fama-French 5-factor alpha, the q -factor alpha, the Barillas-Shanken alpha, the mispricing factor model alpha, and the emotion-imbued behavioral factor model alpha. Newey-West corrected t -statistics (with six lags) are shown in parentheses. The estimation period is from January 1995 to December 2018.

| Panel A: SUE-1 | | | | | | | | | | | Panel B: R11-1 | | | | | | | | | | |
|--|---------------------|---------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--|---------------------|---------------------|---------------------|---------------------|--------------------|--------------------|--------------------|--------------------|---------------------|--|
| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High | |
| m | 0.66*** (2.30) | 0.56** (2.25) | 0.72** (2.58) | 0.80*** (3.30) | 0.87*** (3.64) | 0.84*** (3.42) | 1.06*** (4.59) | 0.90*** (4.22) | 0.96*** (3.93) | 0.99*** (4.06) | -0.55** (-2.13) | 0.11 (0.56) | 0.06 (0.46) | 0.33** (2.55) | 0.30*** (2.68) | 0.35*** (4.24) | 0.29*** (3.32) | 0.43*** (4.59) | 0.34*** (3.31) | 0.60*** (3.10) | |
| α_{FF5} | 0.13 (1.11) | 0.01 (0.15) | 0.10 (0.87) | 0.14 (1.11) | 0.17* (1.90) | 0.20** (2.14) | 0.43*** (3.74) | 0.27*** (3.13) | 0.40*** (3.63) | 0.33*** (3.35) | -0.29 (-0.99) | 0.10 (0.47) | -0.04 (-0.30) | 0.13 (1.24) | 0.13 (1.33) | 0.21** (2.56) | 0.06 (0.78) | 0.25** (2.42) | 0.18 (1.52) | 0.71*** (3.45) | |
| α_{HNZ4} | 0.37*** (3.37) | 0.12 (1.10) | 0.26** (2.28) | 0.26** (1.96) | 0.26*** (2.59) | 0.23** (2.58) | 0.40*** (3.53) | 0.28*** (2.85) | 0.40*** (3.47) | 0.30*** (2.75) | 0.33 (1.06) | 0.51** (2.08) | 0.22 (1.29) | 0.26** (1.97) | 0.26* (1.88) | 0.26*** (2.85) | 0.10 (1.30) | 0.21** (2.23) | 0.08 (0.81) | 0.50** (2.20) | |
| α_{BS6} | 0.39*** (3.96) | 0.11 (1.17) | 0.25** (2.14) | 0.25** (2.13) | 0.27*** (2.66) | 0.26*** (2.92) | 0.41*** (4.04) | 0.28*** (2.87) | 0.40*** (3.94) | 0.32*** (3.14) | 0.45*** (2.98) | 0.61*** (4.96) | 0.30*** (2.70) | 0.31*** (3.62) | 0.28*** (2.98) | 0.25*** (2.61) | 0.09 (1.21) | 0.17* (1.76) | 0.04 (0.42) | 0.44*** (3.44) | |
| α_{SY4} | 0.40*** (3.12) | 0.12 (1.24) | 0.08 (0.71) | 0.29** (2.44) | 0.09 (0.93) | 0.25*** (2.89) | 0.29*** (3.39) | 0.27*** (2.69) | 0.29*** (2.79) | 0.39*** (3.96) | 0.78*** (2.76) | 0.79*** (3.06) | 0.41** (2.21) | 0.44*** (3.37) | 0.37*** (3.20) | 0.24** (2.51) | 0.09 (1.19) | 0.23** (2.26) | 0.03 (0.27) | 0.24 (1.28) | |
| The emotion-imbued behavioral factor model regressions | | | | | | | | | | | The emotion-imbued behavioral factor model regressions | | | | | | | | | | |
| α_{EBF3} | 0.14 (0.97) | -0.06 (-0.49) | 0.09 (0.63) | 0.26** (2.16) | 0.18 (1.36) | 0.30*** (2.73) | 0.60*** (4.22) | 0.13 (0.99) | 0.29*** (2.97) | 0.30** (2.33) | 0.13 (0.50) | 0.35 (1.48) | 0.27 (1.64) | 0.41*** (2.93) | 0.28** (2.42) | 0.13 (0.97) | 0.12 (1.16) | 0.21* (1.76) | 0.08 (0.74) | 0.32** (2.19) | |
| β_{MKT} | 1.04*** (21.62) | 0.95*** (23.44) | 0.98*** (16.21) | 0.95*** (22.99) | 0.95*** (27.52) | 0.92*** (34.93) | 0.92*** (22.81) | 0.91*** (26.58) | 0.94*** (22.22) | 0.96*** (21.94) | 1.26*** (12.08) | 1.11*** (16.49) | 1.03*** (17.99) | 0.97*** (25.30) | 0.92*** (24.18) | 0.94*** (33.31) | 0.89*** (25.62) | 0.91*** (27.27) | 0.95*** (19.43) | 0.99*** (14.15) | |
| B_{FIN} | -0.08 (-0.96) | 0.03 (0.66) | 0.04 (0.73) | 0.02 (0.41) | 0.05 (0.86) | -0.03 (-0.72) | -0.12 (-1.41) | 0.11 (1.58) | -0.13** (-2.56) | 0.01 (0.15) | -0.27 (-1.63) | 0.01 (0.07) | 0.10 (1.20) | 0.18*** (2.72) | 0.20*** (4.19) | 0.23*** (3.65) | 0.20*** (4.43) | 0.17*** (3.23) | 0.09* (1.73) | -0.27*** (-2.77) | |
| β_{PEAD} | -0.34*** (-3.35) | -0.21*** (-2.82) | -0.11 (-1.44) | -0.17* (-1.78) | 0.01 (0.13) | -0.03 (-0.42) | 0.12 (1.15) | 0.06 (0.86) | 0.25*** (2.66) | 0.20** (2.36) | -1.32*** (-4.44) | -0.77*** (-4.39) | -0.65*** (-4.92) | -0.43*** (-4.98) | -0.31*** (-3.53) | -0.09 (-1.48) | -0.05 (-0.61) | 0.12* (1.85) | 0.31*** (4.28) | 0.74*** (5.80) | |
| β_{EMO} | 0.14 (0.96) | 0.21* (1.75) | 0.21* (1.95) | 0.07 (0.60) | 0.14 (1.35) | -0.10 (-0.97) | -0.15** (-2.11) | 0.20 (1.51) | -0.01 (-0.07) | -0.16 (-1.62) | 0.68** (2.38) | 0.33 (1.62) | 0.08 (0.47) | 0.11 (0.85) | 0.12 (1.17) | 0.16 (1.26) | -0.04 (-0.42) | -0.03 (-0.29) | -0.02 (-0.16) | 0.29* (1.84) | |

Table 4. 14: Cash-based Operating Profitability (CbOP) Deciles

The table reports the factor regressions for cash-based operating profitability (CbOP). M , α_{FF5} , α_{HXZ4} , α_{BS6} , α_{SY4} , and α_{EBF3} are the average excess return, the Fama-French 5-factor alpha, the q -factor alpha, the Barillas-Shanken alpha, the mispricing factor model alpha, and the emotion-imbued behavioral factor model alpha. Newey-West corrected t -statistics (with six lags) are shown in parentheses. The estimation period is from January 1995 to December 2018.

| | Low | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High |
|--|---------------------|--------------------|--------------------|---------------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------------------|
| m | 0.25 (0.66) | 0.71** (2.18) | 0.67** (2.33) | 0.87*** (3.21) | 0.83*** (3.72) | 0.93*** (4.05) | 0.88*** (3.67) | 0.93*** (4.36) | 0.86*** (4.00) | 1.05*** (3.85) |
| α_{FF5} | -0.31** (-2.36) | -0.02 (-0.20) | -0.09 (-0.81) | 0.09 (0.80) | 0.04 (0.51) | 0.26** (2.37) | 0.09 (0.78) | 0.22** (2.49) | 0.20*** (2.81) | 0.56*** (5.37) |
| α_{HXZ4} | -0.31** (-2.01) | 0.01 (0.13) | -0.04 (-0.37) | 0.19* (1.67) | 0.11 (1.13) | 0.26** (2.52) | 0.20** (2.01) | 0.29*** (2.78) | 0.27*** (3.59) | 0.60*** (4.71) |
| α_{BS6} | -0.30* (1.92) | -0.00 (-0.03) | -0.06 (-0.58) | 0.18* (1.85) | 0.10 (1.03) | 0.24** (2.33) | 0.19** (1.99) | 0.29*** (3.08) | 0.31*** (4.42) | 0.66*** (6.22) |
| α_{SY4} | -0.17 (-1.14) | 0.19* (1.67) | 0.02 (0.24) | 0.25** (1.98) | 0.10 (1.02) | 0.19 (1.50) | 0.20* (1.75) | 0.28*** (2.68) | 0.24*** (3.16) | 0.52*** (4.37) |
| The emotion-imbued behavioral factor model regressions | | | | | | | | | | |
| α_{EBF3} | -0.33** (-1.97) | -0.21 (-1.38) | 0.03 (0.20) | 0.24 (1.53) | 0.18 (1.53) | 0.36*** (2.98) | 0.11 (0.88) | 0.33*** (3.03) | 0.20** (2.44) | 0.33** (2.49) |
| β_{MKT} | 1.15*** (14.55) | 1.23*** (19.96) | 1.08*** (26.62) | 1.04*** (23.91) | 0.98*** (24.28) | 0.98*** (28.59) | 1.02*** (28.25) | 0.96*** (25.57) | 0.86*** (28.25) | 0.94*** (23.09) |
| β_{FIN} | -0.36*** (-5.47) | 0.07 (1.01) | 0.05 (0.74) | 0.15** (2.19) | 0.17*** (2.61) | 0.11* (1.83) | 0.23*** (3.62) | 0.05 (1.35) | 0.03 (0.64) | -0.14*** (-2.62) |
| β_{PEAD} | -0.15 (-1.59) | -0.16 (-1.27) | -0.17** (-2.02) | -0.31*** (-3.11) | -0.09 (-1.40) | 0.01 (0.16) | -0.11 (-1.53) | -0.03 (-0.56) | 0.07 (1.08) | 0.17** (2.23) |
| β_{EMO} | 0.14 (0.89) | 0.34*** (3.22) | 0.03 (0.31) | 0.16 (1.06) | -0.01 (-0.07) | -0.12 (-1.07) | 0.09 (0.81) | -0.09 (-0.83) | 0.03 (0.35) | 0.25** (2.53) |

Chapter 5

Conclusions and Further Work

It is a truism to say that investor emotions are highly influential in driving their investment decisions. However, whereas the literature has explored the role played by the incidental emotions of mood, sentiment, and uncertainty in asset pricing, the part played by investors deeper or ‘integral’ emotions, such as excitement and anxiety, has only been explored to date in the laboratory. My thesis develops this strand of research and explores how investor fundamental emotions drive real world investor behavior. I show that in line with the emotions in decision-making (Lerner et al., 2015) and object relations theory of psychology (Auchincloss and Samberg, 2012), investors enter into emotional relationships with their stocks, both conscious and particularly unconscious, which have direct asset pricing implications.

I construct a novel market emotion index that captures investor anxiety and excitement, and use it to identify market segments that are more likely to be influenced by variations in these emotions. Specifically, I show highly emotionally charged stocks will dominate stocks with low emotional resonance for investors as investors are attracted and derive more emotional utility from emotional-sensitive stocks. Momentum or trend chasing investors will be more active during up market and contrarian or value investors during down markets. In both cases, the price goes up leading to mispricing.

In Chapter 2, I construct a market emotion index and deriving stock-specific emotion-sensitivity measures using this demonstrate that the stock returns in market segments with high emotion-sensitivity are predictable. A Long-Short emotion beta-based trading strategy generates annualized risk-adjusted abnormal returns of 4.92% during the 1990-2018 period. This evidence of predictability is robust and extends up to four months following the portfolio formation date. This predictability mechanism is also distinct from incidental emotions such as mood, sentiment, uncertainty, and narrative tone. Stocks that are more subject to subjective valuations such as small and growth stocks have a higher emotional charge than large value stocks and this contributes to the emotional utility-driven mispricing I identify.

Next, in Chapter 3, I explore the impact of variations in investor emotion at the local level constructing a local market emotion index, depending on firms' geographic locations. I conjecture local investors may feel emotionally exuberant by reading stories about the state of the stock market in the local press. As local investors prefer local stocks, such emotional exuberance should influence local clienteles' behavior in a coordinated way that leads to return predictability.

If local investors' emotional exuberance about the stock market influences their propensity to invest in local stocks this will also affect their portfolio choices. Excited investors will invest more in local stocks to earn higher future stock returns, whereas anxious investors will sell and drive stock returns down. This mechanism is exacerbated as local investors feel more emotionally proximate about local stocks. In line with this conjecture, I find state portfolios earn high future returns when investors manifest high emotional exuberance as reflected by the local press. During the 1990 to 2018 period, such an emotional exuberance-driven geography-based trading strategy earns an abnormal annualized risk-adjusted return of 9.17%. This local mispricing is stronger for low visibility firms. Nonlocal investors arbitrage away this mispricing in about six months. I demonstrate that local emotional exuberance-driven predictability is distinct from the effects of local narrative tone, sentiment, local optimism, local economic forecasts, and local bias.

Finally, in Chapter 4, I examine the performance of an emotion-imbued behavioral factor model to explain the factor returns of traditional and recently proposed prominent asset pricing models. In addition, I investigate the ability of my emotion-imbued behavioral factor model to explain short- and long-horizon asset pricing anomalies. Integral investor emotions are outside the scope of the standard rational choice model and can directly influence investors decision making (Lerner et al., 2015) despite garnering little or no attention in extant asset pricing models. Drawing on the emotions in decision making and object relations theory literature, I conjecture investors develop emotional relationships with and derive emotional utility from investing in stocks and this creates predictable variation in investor decision-making paving the way for comovement in emotionally-charged stocks. Such predictable variation in investor decision-making is likely to explain different return predictability mechanisms, i.e., market anomalies.

Specifically, I construct an emotion factor using the emotion sensitivity of stocks to variations in an excitement- and anxiety-based market emotion index generated from content

analysis of press coverage of the stock market. This emotion beta factor produces significant monthly factor return of 0.39% with a *t*-statistic of 3.34. Importantly, none of the existing factor models can explain the emotion beta factor returns. My composite market-behavioral-emotional 4-factor model explains most of the factors accounted for by a range of other models. In addition, my emotion-imbued behavioral factor model better explains all the short and long-horizon anomalies identified in the literature.

Overall, my thesis introduces to the literature the role played by often nonconscious investor fundamental emotions in the cross-section of stock returns, and demonstrates how investors become caught up emotionally with stocks and the stock market leading to anomalous market behavior. Also, my research contributes to the news and finance literature as my emotion measure is derived from news articles using a range of emotion keyword dictionaries with clear out-of-sample validity. Finally, I contribute to the emotion and decision-making psychology literature and applied object relations theory in a new domain as I present economically and empirically robust results linking powerful investor nonconscious emotions, i.e., their noneconomic needs and drives, to their investment decisions. In summary, my findings suggest that the role played by investor emotions in equity pricing is difficult to reconcile with extant asset pricing models and can usefully be further explored.

My thesis has identified a rich unexplored seam in the empirical finance literature which I believe has the potential to enhance our understanding of investor and market behavior in a significant way. In my PhD thesis I can only really “scratch the surface” of this new area I have helped to identify together with my supervisors and am aware of the rich panoply of research ideas in empirical emotional finance open to being explored. Three broad research questions I have already begun to think about to work on after my thesis are as follows:

1. Excited investors, lottery-like stocks, and gambling

The finance literature provides empirical evidence that the propensity to gamble and investment decisions are correlated. Investors with gambling proclivities prefer lottery-like stocks. The literature to date explains such behavior in terms of the underlying socio-economic characteristics of investors (Kumar, 2009). However, there is a gap in explaining the emotional needs such investors are meeting in such ‘irrational’ behaviors. Drawing on the psychological literature on the psychopathology of gambling addiction (e.g., Dorn, Dorn, and Sengmuller, 2015), my current research provides a potential way of explaining this phenomenon empirically

in terms of the emotions that such activities generate. I argue that nonconscious ‘excitement’ intensifies investors’ emotional object relationships with lottery-like stocks and meets their underlying psychic needs. Specifically, I conjecture that ‘excited’ investors gamble more and prefer lottery stocks irrespective of their socioeconomic identities.

I am intrigued to see what I can find in the data. I expect to be able to explain the underlying psychological drivers of such economically ‘irrational’ investor gambling behavior in a much richer way.

2. Local investor emotions and stock liquidity

Local investors prefer to invest locally, and the third chapter of my thesis shows how local investors’ emotions drive their stock trading behavior, and explain local return predictability. A natural extension of this finding is to examine the impact of investor emotions on local stock liquidity. I conjecture that local investors enter into object relationships with emotionally proximate local stocks which is acted out in their stock trading decisions and consequently impacts stock liquidity in a predictable manner. Specifically, intensified emotional engagement makes investor behavior more salient at the local level.

Experimental studies show simulated excited investors prefer risky assets (Andrade, Odean, and Lin, 2016) and Grinblatt and Keloharju (2009) show many investors are sensation seekers and invest to experience the thrill. Anxious investors in experimental markets become more fearful (Breaban and Noussair, 2018) and trade less to avoid regret and disappointment (Summers and Duxbury, 2012). Thus, higher local stock emotional utility should lead to higher local liquidity as local investors are likely to trade such stocks more. This conjecture is motivated by the evidence showing segmentation in capital markets (Becker, 2007), preference for local stocks by local investors (Korniotis and Kumar, 2013), emotions in decision-making (Lerner et al., 2015), and psychology-based object relations theory (Auchincloss and Samberg, 2012). To the best of my knowledge, this study would be the first to test investor emotions directly at the state-level to explain local liquidity. I will test this conjecture immediately after submitting my PhD.

3. Investor emotions and corporate decisions

The finance literature shows feelings unrelated to risk can affect corporate and financial decisions and are also prevalent in sophisticated market participants (Taffler, Spence, and Eshraghi, 2017). However, sentiments which are naturally incidental are less context specific and can be attenuated by revealing the attributing sources (Schwarz and Clore, 1983). Integral emotions are more fundamental and have the capability to overwhelm cognitive processes (Lowenstein and Lerner, 2003). Drawing on this line of reasoning, I conjecture that often nonconscious integral manager emotions are an important driving force of corporate financial decisions such as capital investment, M&A, capital structure etc.

Leveraging on my current knowledge on textual analysis it is possible to measure the rich panoply of manager emotions reflected in conference calls and media interviews and comments etc. These go well beyond conventional tone measures of simple positivity/negativity which I will in any case control for. My derived manager emotion variables can then be used to explain different corporate decisions. I will carry out this research agenda starting with developing a new perspective on the ‘non-economic’ psychological and often hidden explanations for M&A activity.

Other potential studies that could follow on from these three, for example, include (i) to explore whether institutional investors integral emotions are as influential in their investment decisions as we show they are for retail investors. In parallel, (ii) the extent to which investment analysts’ forecasts can be better explained by the emotions in decision-making literature and object relations theory than the conventional rational choice model.

Appendix A

Anxiety, Excitement, and Asset Prices

Table 2.A. 1: 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 2.A. 2: Correlation Matrix

The table presents correlation analysis. Panel A presents the correlation between conditional emotion, mood, sentiment, uncertainty, and tone betas. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and Fama-French three-factors—market, size, and value. Then, we take the absolute value of β^{MEI} . The mood beta (β^{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 (β^{SENT}) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. We generate the consumer confidence beta (β^{UMCCI}) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan’s consumer confidence index and Fama-French three-factors. Following Bali et al. (2017), we compute the uncertainty beta (β^{UNC}) by running 60-month rolling regressions of excess stock returns on Jurado et al.’s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta (β^{EPU}) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis’s (2016) economic policy uncertainty index (EPU) and Fama-French three-factors. We derive two tone betas (β^{LM} and β^{HN}) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and Fama-French three-factors. 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 reports correlation between emotion beta and firm characteristics. Firm characteristics are SIZE (log of market capitalization), 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 1995 to December 2018.

Panel A: Correlation between integral and incidental emotion betas

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

Panel B: Correlation between emotion beta and firm characteristics

| | β^{MKT} | β^{VIX} | SIZE | B/M | MOM | REV | ILLIQ | IVOL | I/A | ROE | MAX |
|---------------|---------------|---------------|--------|--------|-------|-------|-------|-------|-------|--------|-------|
| β^{MEI} | 0.124 | 0.005 | -0.261 | -0.052 | 0.187 | 0.028 | 0.047 | 0.290 | 0.128 | -0.146 | 0.249 |

Table 2.A. 3: Fama-MacBeth Regression Estimates: High and Low Mood Period

The table reports the time-series averages of the slope coefficients during high and low mood period obtained from regressing monthly excess stock returns (in percentage) on previous months emotion, mood, sentiment, uncertainty, and tone betas and a set of lagged control variables (used in Table 2.2) using Fama-MacBeth methodology. We determine high and low mood periods following Hirshleifer et al. (2020). Prespecified high mood months are January and March, and low mood months are September and October. The realized extreme positive and negative mood periods are identified using the top two and bottom two months ranked based on the equal-weighted CRSP excess returns realized in a given year. The emotion beta (β^{MEI}) is derived by estimating 60-month rolling regressions of excess stock returns on market emotion index and Fama-French three-factors—market, size, and value. Then, we take the absolute value of β^{MEI} . The mood beta (β^{Mood}) 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 (β^{SENT}) is computed by running 60-month rolling regressions of excess stock returns on Baker and Wurgler (2006) investor sentiment index orthogonalized for macro variables and Fama-French three-factors. We generate the consumer confidence beta (β^{UMCCI}) by estimating 60-month rolling regressions of excess stock returns on the University of Michigan's consumer confidence index and Fama-French three-factors. Following Bali et al. (2017), we compute the uncertainty beta (β^{UNC}) by running 60-month rolling regressions of excess stock returns on Jurado et al.'s (2015) economic uncertainty index and MKT, SMB, HML, MOM, LIQ, I/A, and ROE factors. We estimate the economic policy uncertainty beta (β^{EPU}) by running 60-month rolling regressions of excess stock returns on Baker, Bloom, and Davis's (2016) economic policy uncertainty index (EPU) and Fama-French three-factors. We derive two tone betas (β^{LM} and β^{HN}) by separately estimating 60-month rolling regression of excess stock returns on LM and HN tone and Fama-French three-factors. 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 intercepts and coefficients of lagged control variables. 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.

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

Table 2.A. 4: 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 2.A.1 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 2.A. 5: Proportion of Articles across Emotion 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 ratio of difference between excitement and anxiety word counts to the total of excitement and anxiety word counts. 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 | | | | |
|-----------|---|-------|----------------------|--------------|--------------|--------------|--------------|
| Quintiles | | | 1 | 2 | 3 | 4 | 5 |
| Scores | | | 0.00 | 0.11 | 0.29 | 0.50 | 1.00 |
| Tone | 1 | -0.70 | 0.096 | 0.014 | 0.026 | 0.028 | 0.038 |
| | 2 | -0.47 | 0.077 | 0.022 | 0.040 | 0.036 | 0.028 |
| | 3 | -0.25 | 0.056 | 0.021 | 0.048 | 0.041 | 0.032 |
| | 4 | 0.00 | 0.052 | 0.020 | 0.051 | 0.050 | 0.042 |
| | 5 | 1.00 | 0.030 | 0.013 | 0.039 | 0.051 | 0.049 |

Case Study 2.A. 1: Newspaper Article 1

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

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

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

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

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

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

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

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

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

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

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

Score: MEI 0.50 and LM 0.00

Case Study 2.A. 2: Newspaper Article 2

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Score: MEI -0.40 and LM 0.02

2.A. 1: 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 is available in Taffler et al. (2021).

Appendix B

Emotional Exuberance and Local Return Predictability

Table 3.A. 1: List of Newspapers and Place of Publication

The table presents the list, location, and availability of newspaper headquarters in terms of states and regions, total number of articles, and percentages of articles collected from each newspaper. States and regions represent Census Bureau states and regions and are available from U.S. Census Bureau. All newspapers are divided among four Census Bureau regions. All newspaper articles except for Wall Street Journal are from Nexis. The articles are collected using the power search function and a “relevance score” of 80% or more. Wall Street Journal articles come from ProQuest and in the search function, we use terms ‘Stock Index’, ‘S&P 500’, and ‘Stock Market’, and these need to be present in the abstract, heading, and main text. The sample period is from January 1990 to December 2018.

| | Newspapers | State | Region | Articles | Percent | Availability |
|----|-----------------------------------|----------------------|-----------|----------|---------|--------------|
| 1 | Arizona Capitol Times | Arizona | West | 12 | 0.02 | 2005-2018 |
| 2 | Atlanta Journal Constitution | Georgia | South | 2,406 | 3.74 | 1990-2018 |
| 3 | Augusta Chronicle | Georgia | South | 2,018 | 3.14 | 1993-2018 |
| 4 | Austin American-Statesman | Texas | South | 1,338 | 2.08 | 1994-2018 |
| 5 | Bangor Daily News | Maine | Northeast | 54 | 0.08 | 2005-2018 |
| 6 | Charleston Gazette | West Virginia | South | 645 | 1.00 | 2006-2018 |
| 7 | Chicago Daily Herald | Illinois | Midwest | 755 | 1.17 | 2007-2018 |
| 8 | Colorado Springs Business Journal | Colorado | West | 23 | 0.04 | 2001-2012 |
| 9 | Crain Detroit Business | Michigan | Midwest | 116 | 0.18 | 2001-2018 |
| 10 | Daily Camera | Colorado | West | 83 | 0.13 | 2007-2018 |
| 11 | Daily Journal of Commerce | Oregon | West | 108 | 0.17 | 2002-2018 |
| 12 | Daily News (New York) | New York | Northeast | 817 | 1.27 | 1995-2018 |
| 13 | Dayton Daily News | Ohio | Midwest | 1,754 | 2.73 | 1996-2018 |
| 14 | Indianapolis Business Journal | Indiana | Midwest | 152 | 0.24 | 1996-2013 |
| 15 | Lincoln Journal Star | Nebraska | Midwest | 47 | 0.07 | 2003-2011 |
| 16 | Lowell Sun | Massachusetts | Northeast | 221 | 0.34 | 2001-2018 |
| 17 | Mississippi Business Journal | Mississippi | South | 15 | 0.02 | 2008-2012 |
| 18 | New Orleans CityBusiness | Louisiana | South | 95 | 0.15 | 2001-2018 |
| 19 | New York Post | New York | Northeast | 2,706 | 4.21 | 1997-2018 |
| 20 | New York Times | New York | Northeast | 9,980 | 15.53 | 1990-2018 |
| 21 | Palm Beach Post | Florida | South | 150 | 0.23 | 1994-2000 |
| 22 | Philadelphia Inquirer | Pennsylvania | Northeast | 2,887 | 4.49 | 1994-2018 |
| 23 | Pittsburgh Post-Gazette | Pennsylvania | Northeast | 5,417 | 8.43 | 1993-2018 |
| 24 | Portland Press Herald | Maine | Northeast | 6 | 0.01 | 2008-2011 |
| 25 | Providence Journal | Rhode Island | Northeast | 247 | 0.38 | 2007-2018 |
| 26 | Richmond Times-Dispatch | Virginia | South | 377 | 0.59 | 1996-2018 |
| 27 | S&P Daily News | New York | Northeast | 1,629 | 2.53 | 1990-2017 |
| 28 | Salt Lake Tribune | Utah | West | 1,141 | 1.78 | 1994-2018 |
| 29 | Santa Fe New Mexican | New Mexico | West | 82 | 0.13 | 1995-2008 |
| 30 | Sentinel and Enterprise | Massachusetts | Northeast | 56 | 0.09 | 2006-2018 |
| 31 | South Bend Tribune | Indiana | Midwest | 60 | 0.09 | 2007-2017 |
| 32 | St. Louis Post Dispatch | Missouri | Midwest | 3,907 | 6.08 | 1990-2018 |
| 33 | Star Tribune (Minneapolis) | Minnesota | Midwest | 643 | 1.00 | 1991-2018 |
| 34 | Telegraph Herald | Iowa | Midwest | 333 | 0.52 | 2006-2018 |
| 35 | The (San Jose) Mercury News | California | West | 444 | 0.69 | 2005-2016 |
| 36 | The Bismarck Tribune | North Dakota | Midwest | 329 | 0.51 | 2007-2018 |
| 37 | The Daily Oklahoman | Oklahoma | South | 140 | 0.22 | 2004-2018 |
| 38 | The Detroit News | Michigan | Midwest | 223 | 0.35 | 2007-2018 |
| 39 | The Idaho Business Review | Idaho | West | 28 | 0.04 | 2002-2018 |
| 40 | The Mecklenburg Times | North Carolina | South | 39 | 0.06 | 2008-2018 |
| 41 | The Pantagraph | Illinois | Midwest | 159 | 0.25 | 2007-2018 |
| 42 | The Patriot Ledger | Massachusetts | Northeast | 223 | 0.35 | 1995-2013 |
| 43 | Tulsa World | Oklahoma | South | 4,312 | 6.71 | 1995-2017 |
| 44 | USA Today | Virginia | South | 7,046 | 10.96 | 1991-2018 |
| 45 | Wall Street Journal | New York | Northeast | 3,715 | 5.78 | 1990-2018 |
| 46 | Washington Post | District of Columbia | South | 6,971 | 10.85 | 1990-2018 |
| 47 | Wisconsin State Journal | Wisconsin | Midwest | 369 | 0.57 | 1992-2018 |
| | | | Total | 64,278 | 100 | |

Table 3.A. 2: Correlation between MEIs using Different Keyword Dictionaries

The table reports both Pearson and Spearman rank correlations between our base local market emotion index (MEI) and variations of it constructed using different keyword dictionaries. We construct MEI_{NKT} by counting excitement and anxiety words using Nyman, Kapadia, and Tuckett (2021) word lists. We follow Nyman et al. (2021) to orthogonalize our MEI measure to macro-related news. In addition to Nyman et al.'s (2021) 'boost', 'boosts', and 'boosted' we also exclude 'boost', 'boosts', 'boosting', 'boosted', 'booster', 'expand', 'expands', 'expanding', 'expanded', 'expansion' from our excitement dictionary, and we exclude 'shrink', 'shrinks', 'shrinking', 'shrunk', 'shrinkage', in addition to 'uncertain', and 'uncertainty' from our anxiety word lists to construct $MEI_{Ext.Macro}$. p -values are beneath the correlation coefficients. The sample period is January 1990 to December 2018.

| | | MEI | |
|-----------|-------------------|------------------|------------------|
| | | Pearson | Spearman |
| Northeast | MEI_{NKT} | 0.648 (0.000) | 0.673 (0.000) |
| | $MEI_{Ext.Macro}$ | 0.995 (0.000) | 0.995 (0.000) |
| Midwest | MEI_{NKT} | 0.556 (0.000) | 0.528 (0.000) |
| | $MEI_{Ext.Macro}$ | 0.993 (0.000) | 0.989 (0.000) |
| South | MEI_{NKT} | 0.700 (0.000) | 0.655 (0.000) |
| | $MEI_{Ext.Macro}$ | 0.974 (0.000) | 0.979 (0.000) |
| West | MEI_{NKT} | 0.466 (0.000) | 0.456 (0.000) |
| | $MEI_{Ext.Macro}$ | 0.991 (0.000) | 0.991 (0.000) |

Table 3.A. 3: Summary Statistics: Local MEI

The table reports summary local market emotion index (MEI) statistics by region by in Panel A. Also, in Panel B, the table reports correlations between local and U.S.-level emotional exuberance and Baker and Wurgler (2006) investor sentiment, University of Michigan's Consumer Confidence Index, Loughran and McDonald (2011, LM), and Henry (2008, HN) positive/negative-based tone measures. The sample period is January 1990 to December 2018.

| Panel A: Summary Statistics | | | | |
|-----------------------------|---------------------------------|---------|--------|--------|
| | Northeast | Midwest | South | West |
| <i>State MEI:</i> | | | | |
| Mean | 0.199 | 0.178 | 0.157 | 0.205 |
| Std. Dev. | 0.068 | 0.089 | 0.076 | 0.208 |
| Min | -0.007 | -0.033 | -0.047 | -0.214 |
| Max | 0.398 | 0.445 | 0.325 | 0.867 |
| Panel B: Correlation | | | | |
| | U.S.-level emotional exuberance | | | |
| | Northeast | Midwest | South | West |
| State MEI | 0.229 | 0.255 | 0.349 | 0.102 |
| | US-level Investor Sentiment | | | |
| | Northeast | Midwest | South | West |
| State MEI | 0.009 | 0.152 | 0.128 | 0.078 |
| | Consumer Confidence Index | | | |
| | Northeast | Midwest | South | West |
| State MEI | 0.035 | 0.051 | 0.047 | -0.127 |
| | U.S.-level LM Tone | | | |
| | Northeast | Midwest | South | West |
| State MEI | 0.219 | 0.195 | 0.117 | 0.156 |
| | U.S.-level HN Tone | | | |
| | Northeast | Midwest | South | West |
| State MEI | 0.246 | 0.219 | 0.203 | 0.066 |

Table 3.A. 4: Panel Predictive Regression Estimates controlling US-level Emotional Exuberance

The table reports the results from panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X_{j,t-1}^{MEI}\delta_1 + X_{j,t-2}\delta_2 + X_{USA,t-2}\delta_3 + \log(1 + D/P)_{j,t-1}\delta_4 + \varepsilon_{j,t}$. Specifically, we predict the quarterly state portfolio return in quarter t using lagged state-level market emotion index, U.S.-level emotional exuberance (US MEI) and macroeconomic variables measured in quarter $t - 1$ or $t - 2$. The dependent variable $Y_{j,t}$ is the difference between the state return and a benchmark return. In columns (1) to (4), the dependent variable is the characteristic-adjusted return computed using the Daniel, Grinblatt, Titman, and Wermers (1997, DGTW) method. The row vectors $X_{j,t-1}^{MEI}$ contain the state market emotion index. The row vectors $X_{j,t-2}$ and $X_{USA,t-2}$ contain the state- and U.S.-level predictors, respectively. The predictability regressions are estimated using OLS. The t -statistics are reported in parentheses beneath the estimates use serial and cross-sectional correlation adjusted Driscoll and Kraay (1998) standard errors. The estimation period is from 1990 to 2018.

| Predictor | Benchmark for Computing Residual Return | | | |
|--|---|-------------------|-------------------|-------------------|
| | DGTW (1) | DGTW (2) | DGTW (3) | DGTW (4) |
| <i>Main Predictors</i> | | | | |
| State MEI | 0.025 (2.62) | 0.023 (2.15) | 0.025 (2.53) | 0.023 (2.11) |
| <i>State-level Business Cycle Predictors</i> | | | | |
| State Inc Gr | | 0.014 (0.14) | 0.015 (0.15) | 0.017 (0.17) |
| State Rel Un | | 0.018 (3.26) | 0.013 (2.20) | 0.013 (2.03) |
| State hy | | -0.008 (-1.02) | -0.004 (-0.55) | -0.006 (-0.75) |
| <i>US-level Market Emotion Index</i> | | | | |
| US MEI | 0.005 (1.25) | 0.004 (1.21) | 0.004 (1.11) | 0.001 (0.31) |
| <i>Other Predictors</i> | | | | |
| $\log(1+D/P)$ | | | | 0.268 (2.18) |
| US Inc Gr | | | -0.022 (-0.17) | -0.015 (-0.13) |
| US Rel Un | | | 0.022 (0.96) | 0.002 (0.08) |
| US hy | | | -0.099 (-1.66) | -0.191 (-2.12) |
| US cay | | | | -0.697 (-1.87) |
| Paper-Bill Spd | | | | 0.512 (1.06) |
| Term Spd | | | | 0.747 (1.65) |
| Default Spd | | | | -0.164 (-0.36) |
| Adj. R^2 | 0.025 | 0.026 | 0.027 | 0.033 |
| N obs | 5028 | 5028 | 5028 | 5028 |

Appendix C

An Emotion-imbued Behavioral Factor Model

Table 4.A. 1: List of Newspapers

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. Wall Street Journal articles come from ProQuest. 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 |

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