Emotional Exuberance and Local Return Predictability

Shehub Bin Hasan, Alok Kumar, and Richard Taffler[1]

Abstract

This study explores 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, we show an investor emotion-driven geography-based trading strategy generates an annualized alpha of 9.17% during the 1995 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 we exclude large states, oil-producing and consuming states, and states with large dominant firms. Collectively, the findings demonstrate that local investors obtain additional emotional utility from investing in local stocks, and this is an important determinant of local asset prices.

Keywords: Emotion, geography-based trading strategy, emotional utility, return predictability.

JEL classification: G12, G14

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Abstract

This study explores 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, we show an investor emotion-driven geography-based trading strategy generates an annualized alpha of 9.17% during the 1995 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 we exclude large states, oil-producing and consuming states, and states with large dominant firms. Collectively, the findings demonstrate that local investors obtain additional emotional utility from investing in local stocks, and this is an important determinant of local asset prices.

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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.[1] 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 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.

[1] 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).

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. Kuhnnen 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 one of the key 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.[2]

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

[2] 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.

(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 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. Also, we control for U.S.-wide market emotion index to tease out the incremental predictability of local market emotion index.

We test state portfolio return predictability by estimating panel fixed effects regressions using quarterly data for 1990 to 2018.[3] 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,

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

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 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 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.

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. 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.

3.1 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 A1 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.[4] Socioeconomic homogeneity is the principal criterion employed in grouping states into regions.[5] 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 (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 A1 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

[4] https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf
[5] https://www2.census.gov/geo/pdfs/reference/GARM/Ch6GARM.pdf

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.

3.2 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 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.[6] Investor sentiment data is from Jeffrey Wurgler's website.[7]

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.[8] 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.[9]

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.

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[6] https://fred.stlouisfed.org/series/UMCSENT

[7] http://people.stern.nyu.edu/jwurgler/

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

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

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.

3.6 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 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:

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

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.

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.

3.7 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, Odin, 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.[10] 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.[11] Finally, in our predictability regressions we control for several state-level macro predictors that capture the local macroeconomic environment such as state-

[10] We thank Rickard Nyman for supplying us with the word lists. Table A2 provides detailed correlation coefficients.

[11] 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', 'shrunken', 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 A2 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 0.06 and -0.02, respectively. 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.[12]

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.

3.8 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 $t-2$:

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

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 $X^{MEI}_{j,t-1}$ 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.-

[12] 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:

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

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 1 presents summary statistics for quarterly state returns and all state- and U.S.-level return predictors.[13] 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

[13] We also present summary statistics of local MEI across the US geographic regions in Panel A of Table A3. On average, local MEI is similar in magnitude across all four US 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 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.[14] Table 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.

4.1 Return predictability regression estimates

[14] We also examine the correlation between our local emotional exuberance with US-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 US-level measures (see Panel B of Table A3).

Table 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). 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 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.[15] 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 are similar to our baseline estimates. The average of the state market emotion index coefficient estimates is 0.021 and is statistically significant in 80% of cases. The

[15] We also perform a 3-year recursive estimate and find qualitatively similar results.

result indicates that the evidence of predictability is strong even when we estimate predictability regression recursively.

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.

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.[16] 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.

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

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

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.

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, column (4), and include four states in the extreme "Long" and "Short" portfolios. Figure 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 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 1 and 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.

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 4 Panel A reports average raw, market-adjusted, and characteristic-adjusted returns. We also report performance estimates for the "Others" portfolio. Figure 3 provides performance estimates for the 1995 to 2007 and 2008 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 irrespective of the choice of performance measure. Specifically, the evidence in Table 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.[17]

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 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%.

4.2.4 Conditional factor model performance estimates

[17] 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.

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 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.

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 arbitraged 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 varies.

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 arbitraging 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:

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

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 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.

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 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 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.

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 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.

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.[18]

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).[19]

Table 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 and state relative unemployment together subsume the predictability power of the tone

[18] 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.

[19] 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.

measures. Therefore, it is reasonable to assert that the emotional exuberance measure is teasing out something distinct from narrative tone.

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 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.

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.[20]

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 9 column (3) includes local small business optimism, and we still find that our integral emotion-driven exuberance has significant predictive ability at

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

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

4.5.4 Is emotional exuberance capturing local economic activity forecast?

Local economic activity plays a significant role is 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).[21]

In column (4) of Table 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.

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 Porteba, 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.[22] 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 a local bias-based measure in our predictive regressions. In line with Hong, Kubik, and Stein (2008), we define local bias as RATIO, which is the total of book value

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

[22] 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.

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.

Table 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 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.

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 or region, 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.

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 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.

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.

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:

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

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:

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

We re-estimate our predictability regression using these two alternative measures and present the coefficients in rows (10) and (11) of Table 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.

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 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.

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 Bin Hasan et al. (2021).

We report the results of our predictability regressions after controlling for the market emotion index in Appendix Table A4. 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.[23]

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.

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.

4.7.1 Alternative prediction models

[23] 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.

Panel A of Table 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 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 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.

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 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.

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 arbitraged 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.

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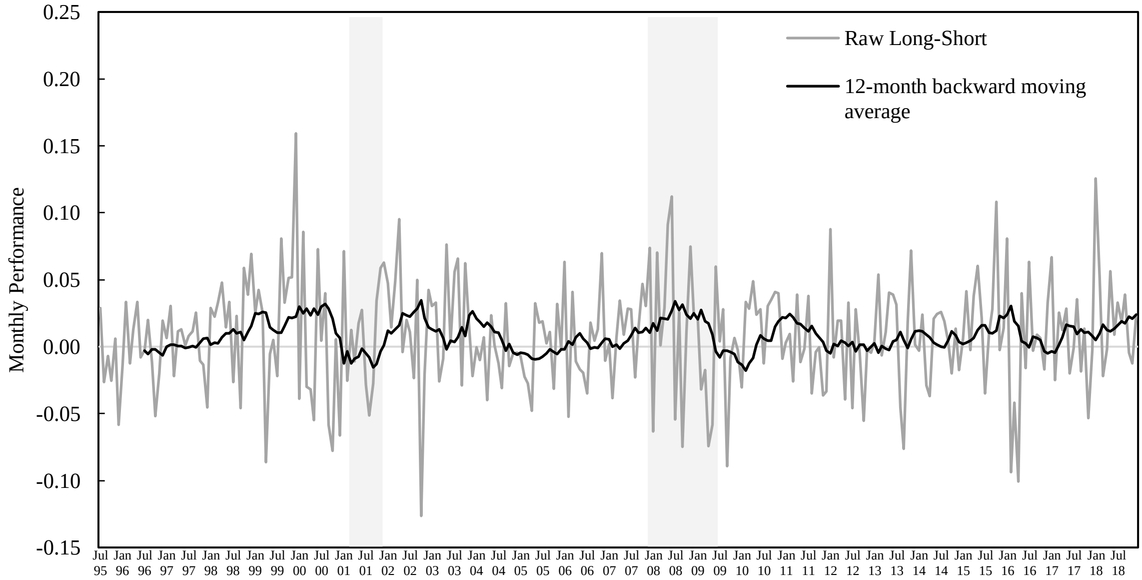
Panel A: Raw return



Panel B: Characteristic-adjusted return

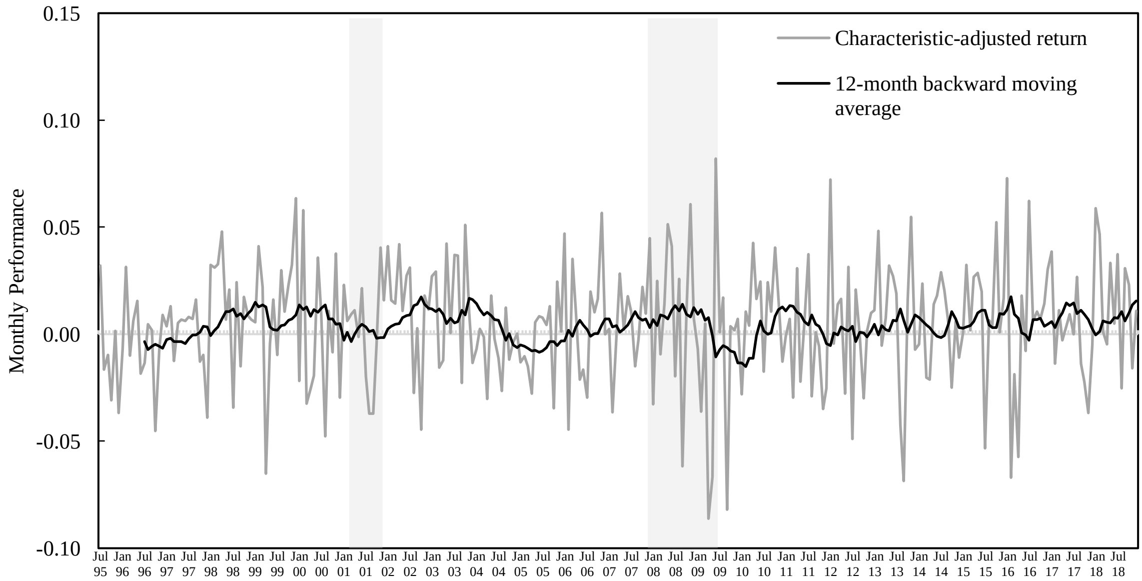


Figure 1: Monthly trading strategy performance time series. The figure shows the raw (Panel A) and characteristic-adjusted (Panel B) performance time series for our geography-based Long-Short trading strategy described in Table 4. The light line indicates the monthly performance measure, and the dark 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 column (4) and the only difference is using a recursive estimate. The shaded regions are recession periods based on NBER recession indicators.

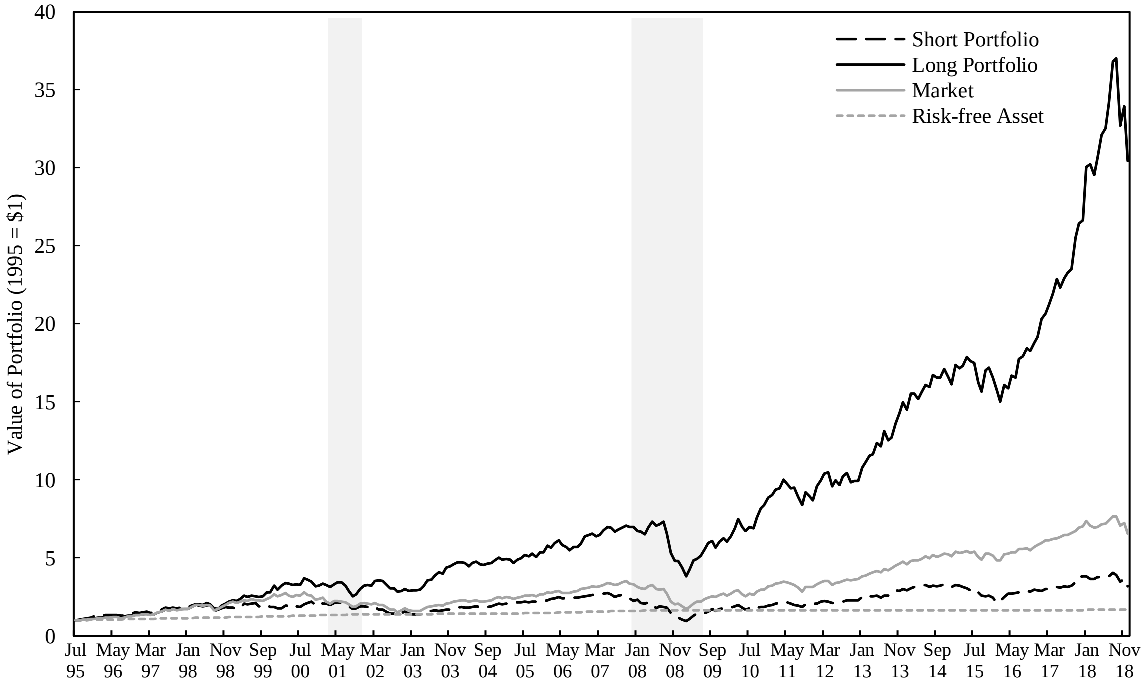


Figure 2: Performance of geography-based long and short portfolios versus the market. The figure shows the relative performance of Long and Short portfolios along with the performance of the aggregate stock market. The construction of the portfolios is described in the caption of Table 4, where the portfolios are formed using the baseline predictability model presented in Table 3 column (4). The shaded regions are recession periods based on NBER recession indicators. The estimation period is from July 1995 to December 2018.

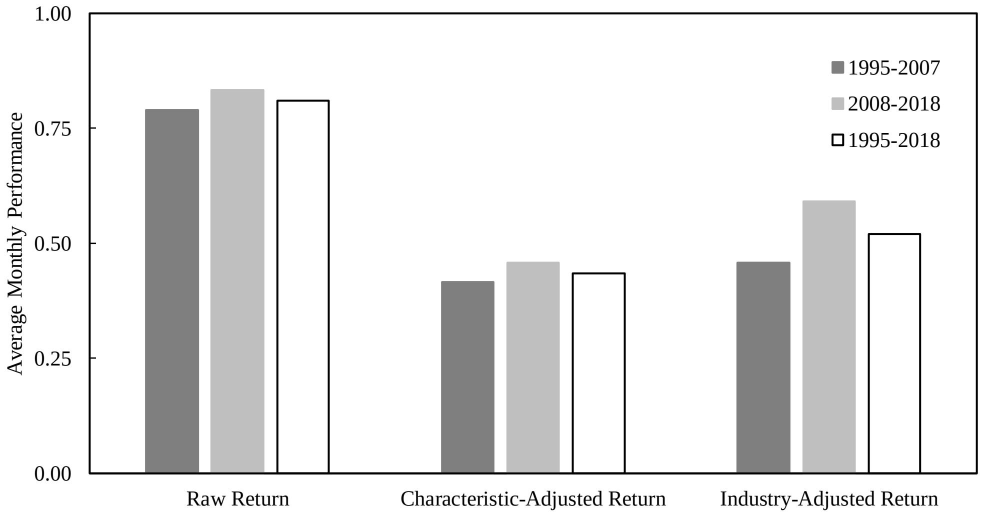


Figure 3: Subsample estimates. The figure shows the raw, characteristic, and industry-adjusted performance estimates of our baseline Long-Short trading strategy evaluated over different subperiods. The construction of the portfolios is described in the caption of Table 4 and the portfolios are formed using the baseline predictability model presented in Table 3 column (4). The evaluation period is from July 1995 to December 2018.

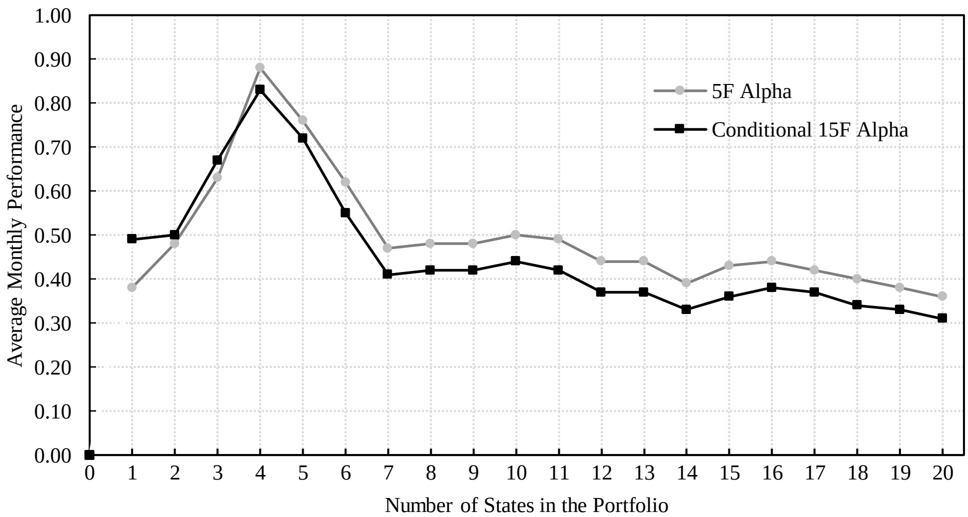


Figure 4: Sensitivity to the number of states in the extreme portfolios. The figure presents the alpha estimates for the Long-Short portfolio as the number of states in the extreme portfolios varies from 1 to 20. The construction of the portfolios is described in the caption of Table 4 and the portfolios are formed using the baseline predictability model presented in Table 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 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 A1 that covers four U.S. census regions. The state market emotion index, which measures local emotional exuberance, 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 *hy*	-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 *hy*	-0.083	0.083	0.981
Dividend-to-Price Ratio	*log(1+D/P)*	0.019	0.010	0.942
U.S. *cay* Residual	US *cay*	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 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 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(1+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: 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.

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

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

Table 4: Continued.

Panel B: Unconditional factor model estimates.

	Portfolio											
Factor	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	-0.302	0.821	0.494	-0.179	0.673	0.534	-0.348	0.882	0.532	-0.232	0.764
	(4.02)	(-2.01)	(4.06)	(3.89)	(-1.20)	(3.51)	(3.92)	(-2.38)	(4.50)	(3.89)	(-1.51)	(4.10)
RMRF	1.005	0.978	0.026	1.018	0.913	0.104	0.997	1.003	-0.005	1.022	0.967	0.055
	(25.36)	(21.91)	(0.41)	(25.97)	(21.60)	(1.74)	(24.41)	(19.16)	(-0.08)	(23.92)	(18.26)	(0.78)
SMB	0.155	-0.045	0.201	0.151	-0.025	0.176	0.154	-0.049	0.204	0.156	-0.030	0.186
	(2.68)	(-0.73)	(2.29)	(2.56)	(-0.42)	(1.96)	(2.19)	(-0.61)	(1.70)	(2.19)	(-0.44)	(1.74)
HML	0.077	0.472	-0.395	0.091	0.401	-0.309	0.098	0.401	-0.302	0.132	0.265	-0.133
	(1.24)	(5.94)	(-4.81)	(1.44)	(4.18)	(-2.58)	(1.38)	(3.64)	(-2.20)	(1.68)	(2.78)	(-1.08)
UMD				0.035	-0.171	0.206				0.033	-0.193	0.227
				(0.87)	(-2.22)	(2.90)				(0.88)	(-2.75)	(3.33)
RMW							-0.011	0.016	-0.027	-0.021	0.100	-0.121
							(-0.14)	(0.16)	(-0.19)	(-0.25)	(1.03)	(-0.86)
CMA							-0.042	0.155	-0.197	-0.062	0.158	-0.221
							(-0.32)	(1.06)	(-0.95)	(-0.43)	(1.00)	(-0.94)
STR										-0.053	-0.058	0.007
										(-0.89)	(-1.05)	(0.06)
LTR										-0.016	0.096	-0.111
										(-0.17)	(0.77)	(-0.63)
LIQ										-0.022	-0.025	0.004
										(-0.52)	(-0.37)	(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 5: Performance of trading strategies using 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 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.

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

Table 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 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.

	Quarters Ahead			
Portfolio	h = 1	h = 2	h = 4	h = 8
Long	0.532	0.534	0.098	0.016
	(3.89)	(4.14)	(0.73)	(0.12)
Short	-0.232	-0.158	-0.209	-0.315
	(-1.51)	(-0.97)	(-1.33)	(-1.81)
Long-Short	0.764	0.692	0.307	0.331
	(4.10)	(3.94)	(1.61)	(1.40)
N months	282	279	273	261

Panel B: Monthly conditional alpha estimates.

	Quarters Ahead			
Portfolio	h = 1	h = 2	h = 4	h = 8
Long	0.401	0.393	0.077	-0.088
	(2.99)	(3.24)	(0.65)	(-0.70)
Short	-0.311	-0.124	-0.227	-0.314
	(-1.84)	(-0.74)	(-1.39)	(-1.82)
Long-Short	0.712	0.517	0.304	0.226
	(3.30)	(2.49)	(1.52)	(1.00)
N months	282	279	273	261

Table 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 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 ($h = 1$).

	Visibility	
Portfolio	Low	High
Long	0.386	0.426
	(1.87)	(2.42)
Short	-0.372	-0.006
	(-1.45)	(-0.03)
Long-Short	0.757	0.432
	(2.56)	(1.74)

Panel B: Subsequent correction ($h \geq 1$).

h	Low	High
1	0.757	0.432
	(2.56)	(1.74)
2	0.624	0.269
	(2.23)	(1.00)
4	0.499	0.262
	(1.63)	(1.00)
8	0.373	0.235
	(0.99)	(0.86)

Table 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 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.

	Portfolio			
State characteristics and demographics	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 *hy*	-0.066	-0.059	0.032	-0.098
				(-3.83)
log(1+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 9: Panel predictive regression estimates.

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.

	Benchmark for Computing Residual Return						
Predictor	DGTW (1)	DGTW (2)	DGTW (3)	DGTW (4)	DGTW (5)	DGTW (6)	DGTW (7)
Main Predictor							
State MEI	0.018	0.019	0.021	0.021	0.020	0.018	0.018
	(2.08)	(2.16)	(2.38)	(2.47)	(2.39)	(2.44)	(2.35)
State-level Business Cycle Predictors							
State Inc Gr	0.019	0.009	0.007	0.013	0.013		0.005
	(0.20)	(0.09)	(0.07)	(0.14)	(0.14)		(0.05)
State Rel Un	0.012	0.012	0.014	0.013	0.012		0.013
	(1.94)	(1.95)	(2.29)	(1.91)	(1.95)		(2.15)
State *hy*	-0.006	-0.007	-0.007	-0.006	-0.006		-0.007
	(-0.66)	(-0.73)	(-0.79)	(-0.61)	(-0.68)		(-0.76)
Tone-based Predictors							
State LM	0.001					0.001	0.002
	(0.04)					(0.13)	(0.17)
State HN	0.009					0.005	0.003
	(0.64)					(0.41)	(0.27)
Sentiment-based Predictors							
Investor Sentiment		0.009				0.008	0.008
		(0.87)				(0.80)	(0.77)
Consumer Confidence Index		0.076				0.076	0.076
		(2.71)				(2.85)	(2.90)
Small Business Optimism			0.001			0.001	0.001
			(1.33)			(0.68)	(1.06)
State Leading Index				0.001		0.001	0.001
				(0.35)		(0.21)	(0.24)
Local Bias-based Predictor							
RATIO					-0.056	-0.092	-0.100
					(-0.29)	(-0.50)	(-0.54)
Other U.S.-level Predictors	Yes	No	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.029	0.032	0.029	0.028	0.029	0.031	0.031
N obs	5028	5028	5028	5028	5028	5028	5028

Table 10: Panel predictive regression estimates.

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 and are available in the caption of that table. Test (1) is the baseline coefficient presented in Table 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 11: Trading strategy performance estimates from 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 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 20^{th} 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	0.224	0.276	0.287
	(1.73)	(1.65)	(2.10)	(2.07)
Short	-0.352	-0.245	-0.436	-0.321
	(-2.30)	(-1.58)	(-2.83)	(-1.81)
Long-Short	0.593	0.469	0.712	0.608
	(2.83)	(2.16)	(3.25)	(2.59)

Table 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	0.305	0.372	0.284
	(0.74)	(2.53)	(2.70)	(1.95)
Short	-0.547	-0.351	-0.317	-0.194
	(-3.62)	(-2.14)	(-2.30)	(-1.32)
Long-Short	0.665	0.656	0.689	0.478
	(2.80)	(3.17)	(3.51)	(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	0.634	0.448	0.412
	(2.79)	(3.23)	(3.29)	(3.05)
Short	-0.246	-0.120	-0.280	-0.304
	(-1.25)	(-0.62)	(-1.64)	(-1.81)
Long-Short	0.648	0.754	0.728	0.716
	(2.84)	(2.87)	(3.32)	(3.31)

Appendix A

Table A1: 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 A2: 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', 'shrunken', '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 A3: 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 US-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
State MEI:				
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				
	US-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
	US-level LM Tone			
	Northeast	Midwest	South	West
State MEI	0.219	0.195	0.117	0.156
	US-level HN Tone			
	Northeast	Midwest	South	West
State MEI	0.246	0.219	0.203	0.066

Table A4: Panel Predictive Regression Estimates controlling US-level Emotional Exuberance

The table reports the results from panel predictive regressions of the form: $Y_{j,t} = \alpha_j + X^{MEI}_{j,t-1}\delta_1 + X_{j,t-2}\delta_2 + X_{USA,t-2}\delta_3 + log(1 + D/P)_{j,t-1}\delta_4 + \varepsilon_{j,t}$. Specifically, we predict the quarterly state portfolio return in quarter t using lagged state-level market emotion index, US-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 $X^{MEI}_{j,t-1}$ 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.

	Benchmark for Computing Residual Return			
Predictor	DGTW (1)	DGTW (2)	DGTW (3)	DGTW (4)
Main Predictors				
State MEI	0.025	0.023	0.025	0.023
	(2.62)	(2.15)	(2.53)	(2.11)
State-level Business Cycle Predictors				
State Inc Gr		0.014	0.015	0.017
		(0.14)	(0.15)	(0.17)
State Rel Un		0.018	0.013	0.013
		(3.26)	(2.20)	(2.03)
State *hy*		-0.008	-0.004	-0.006
		(-1.02)	(-0.55)	(-0.75)
US-level Market Emotion Index				
US MEI	0.005	0.004	0.004	0.001
	(1.25)	(1.21)	(1.11)	(0.31)
Other Predictors				
log(1+D/P)				0.268
				(2.18)
US Inc Gr			-0.022	-0.015
			(-0.17)	(-0.13)
US Rel Un			0.022	0.002
			(0.96)	(0.08)
US *hy*			-0.099	-0.191
			(-1.66)	(-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