The Variability of Emotions: Behavioral Risk or Mispricing

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Abstract

In this study, we examine the effect of behavioral arousal risk, measured by idiosyncratic volatility of emotions (EMO), on asset prices. Portfolio and multivariate approach are implemented to explore the correlation between cross section stock returns and EMO. Results suggest that an increase in EMO is associated with substantial annualized alpha (5.30%) and excess return growth (7.20%). Further evidence shows that idiosyncratic volatility of emotions captures the risk premium of stock returns but is uncorrelated with mispricing by regressing EMO with decomposed risk and mispricing components. This suggests that idiosyncratic volatility of emotions is a distinct phenomenon from the idiosyncratic volatility anomaly (Ang et al., 2006; 2009). Additionally, we find that high institutional ownership (informed trader) shows less pricing effect of behavioral risk, which suggests that the source of behavioral risk is from noise trading instead of informed trading. Overall, the cross-section evidence supports that arousal driven noise trading risk is compensated by premia.

Keywords: Behavioral risk, Arousal, Idiosyncratic volatility of emotions, Noise trading, Cross-section return

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“The markets are moved by animal spirits, and not by reason.” - John Maynard Keynes, 1936

1. Introduction

The role of affect has become a significant hype in asset pricing research, yet empirical evidence in supporting its association with market risk is limited. The "animal spirits", defined as "a spontaneous urge to action rather than inaction" (Keynes, 1936), refers to affective arousal drives the individuals’ buying and selling security in an ever changing and uncertain market. Emotion charged arousal intertwines with investors’ cognitive evaluation of information, signals and risk in the market, thus it contributes to the price formation process. Psychologists classify emotion into valence (positive vs. negative) and arousal (intensity) (Posner et al., 2005). Financial studies have documented evidence that sentiment (valence) affects asset empirical regularities, such as return (Tetlock, 2007; Tetlock et al., 2008; Edmans et al., 2022; Obaid and Pukthuanthong, 2022) and volatility (Lee, 2002); in which a large portion of the valence effect is attributed to mispricing. However, the other aspect of emotion, intensity, in pricing is non-trivial but not yet much explored. The “animal spirits” risk manifested in the market reflects an aggregation of impulsive behaviors of investors that rooted in their emotional urge or arousal. Quantitatively, emotional arousal could be measured by the intensity - variability of emotions in lieu of positive vs. negative emotions. In this research, we investigate the association between cross-section stock return and emotion arousal, also referred as behavioral arousal risk.

When one discusses financial risk, the first impression is uncertainty in the valuation of economic fundamentals, which is commonly measured by variance or volatility of returns (Merton, 1987). Schwert (1989) studied the volatilities of stock and bond returns as well as macroeconomic variables, and considered those volatilities as risk pricing factors. Since aggregate market risk is only significant when the capital asset pricing complied with an efficient market theory, the idiosyncratic volatility becomes a vital measure to capture the firm specific risk in a less diversified capital market. Pontiff (2006) suggests that idiosyncratic risk is the single largest cost faced by arbitrageurs. Campbell et al. (2001) documented that firm idiosyncratic volatility plays a risk pricing role and displays a positive trend between 1962 and 1997. However, Ang et al. (2006) provided empirical evidence that high stock idiosyncratic volatilities lead to low future expected returns. In addition to the uncertainty of fundamentals, the variability of emotions is an important behavioral component in asset pricing to be reckoned with. Hirschilerifer (2001) posited that misperceptions are strongest in the idiosyncratic corners of the marketplace. Accordingly, we consider idiosyncratic volatility of news and social media emotions constructed similarly to idiosyncratic volatility of excess returns (Ang et al., 2006; 2009) as an emotional variability measure. Further, we propose this novel idiosyncratic risk measured by using the variability of emotion innovations, as an indicator for behavioral arousal risk. To investigate whether emotional volatility is priced as a risk indicator or mispricing factor can offer new empirical insights in addition to fundamental risk valuation. Thus, we empirically test the cross-section stock return and a novel idiosyncratic volatility of emotions (*EMO*), which represents the variability of individual investors' emotions comparing to market emotion in a less efficient market.

Emotion charged arousal is a source of noise trading. Unlike the sentiment in biasing the information process, it contributes to investors' impulsive decisions, such as the casino instinct (Loewenstein and Lerner, 2003), in gambling by chances and risking money on uncertain outcomes. As the intensity of noise trading in the market increases, the casino instinct of investors damages the interlink between capital market and real economy but heightens the odds of financial crisis (Wojnilower, 1980; DeLong et al.,1990). Thus, the continuous exploration of pricing the gambling risk from the casino instinct of noise traders is crucial for hedging short lived behavioral risks in financial markets. There two facets of noise trader risk: (1) mispricing - noise as the unexplained component of total return variation, and (2) behavioral risk - the short-run risk faced by arbitrageurs engaged in long-short pairs trading (Scruggs, 2007). In a traditional non-arbitrageable noise trading market, two assumptions are made: "non fundamental" shocks press prices away from security value; there is a limit to arbitrage (Shleifer and Vishny, 1997). The positive/negative sentiment has been considered as a proxy of portions of noise traders pressing prices away from market equilibrium that also costly to arbitrage. The mispricing aspect of noise trading has been supported by empirical evidence from news sentiment pressure (Tetlock 2007, 2008), flight to liquidity (Acharya and Pedersen, 2005), and asset price bubbles (Griffin et al., 2011). These research have considered behavioral bias/noise trading risk as market mispricing. On the other hand, the behavioral risk component of noise traders has been validated by recent studies. Yang et al. (2020) measured abnormal idiosyncratic volatility as an information risk indicator and documented that the information risk is priced. Additionally, Huang et al. (2022) utilized flow-driven noise trading risk as a state variable and found that future factor risk premia are positively related to noise trading risk. To study an arbitrageable noise trading market is of interests to proactive asset managers during high uncertainties. Let us say, the random bets of noise traders deviate asset prices away from their fundamental values; however, the participations of arbitrageurs are still active in condition of a premium earned by bearing economic risks plus behavioral uncertainties. In this case, it becomes necessary to empirically evaluate the noise trading intensity in pricing asset risk premium under a casino market. In that regard, our research aims to test whether the idiosyncratic emotion risk is priced and to what extent the cross-section stock risk premium is compensated by *EMO*.

To further explain the link between behavioral arousal risk and noise trading, hereby, a brief theoretical ground is laid. Assuming the simplest scenario that 1) the market is made of arbitrageurs and noise traders; 2) fundamental determinants and expected future dividends are not changing (DeLong et al.,1990). With noise traders absent, set both μ (mean) and σ^2 (variance) equal to zero, the price of an asset is always equal to its fundamental value. However, with noise traders present, the asset price is excessively volatile that it moves more than can be explained by changes of fundamentals. Additionally, the intensity of noise trading determines the level of non-fundamental demand contributing to excessive volatilities. Thus, the idiosyncratic volatility of residuals becomes more relevant in explaining noise trading driven risk than fundamental risk. Supposing noise traders' psychology are non-serial correlated, then we could purge the idiosyncratic portion of firm specific emotions from the market wide emotions to approximately assess noise trading activities. Subsequently, the noise trading intensity is measured by taking the higher moment of the previously calculated idiosyncratic residuals of emotions. Built on the behavioral arousal risk proposition, our proposed EMO aims at capturing the risk patterns from emotion-driven noise trading.

Our insight is developed from several key observations of investor emotion. First, psychologists believe that emotions affect the investors' assessment of risk and monetary value of investment securities (Lerner and Keltner, 2000; Han, Lerner and Keltner, 2007). Second, Hirschilerifer (2001) summarizes that emotion plays important roles in ambiguity aversion, risk preferences and discount rate (intertemporal choices) as considerations of risk return tradeoffs. Third, Kuhnen and Knutson (2011) find that investors in a positive emotional state will adopt relatively higher risk-seeking strategies by holding riskier portfolios compared to investors in a negative emotional state. Furthermore, appraisal theorists contend that the specific emotions of the same valence could have different effects on decision making, such as a person's appraisal or cognitive response to a specific situational change. For instance, fear promotes pessimistic risk estimates and risk-averse choices, while anger encourages optimistic risk estimates and risk-seeking choices (Lerner and Keltner, 2001; Tiedens and Linton, 2001). Combining the above observations suggests that emotions impact security risk and price formation and influence investors' portfolio choices through various channels. Our study is motivated by emotion observations, but to offer a first empirical analysis of emotion intensity (animal spirit) on idiosyncratic risk in asset pricing. We estimate the EMO by first to regress the firm specific emotion on the market emotion, then to take the square of the idiosyncratic residual of emotion. This approach is similar to the idiosyncratic volatility calculation by Ang et al. (2006, 2009). The adopted emotion index is constructed by taking the first principal component of ten basic emotions (optimism, joy, love/hate, trust, anger, conflict, gloom, fear, stress and surprise) from Thomson Reuters MarketPsych Indices (TRMI). TRMI encompasses a comprehensive set of asset specific psychology proxies that measured by textually analyzing a collection of finance-related media information and opinions. It covers three content sources, including news, social media, and the combination of both.

First, we implement portfolio and cross-sectional empirical tests to examine whether *EMO* is priced into stock returns. We demonstrate *EMO* single sorted and double sorted monthly portfolio performances. The *EMO* sorted portfolio earns a positive alpha and appears to be significant both statistically and economically. The double sorted portfolios of High-minus-Low EMO with size and book-to-market (B/M) ratio also generate positive risk adjust alphas. The result verifies that the positive relationship between *EMO* and stock returns is not driven by firm characteristics, such as size or B/M ratio. Furthermore, we perform multivariate analysis of EMO on the next period cross section return followed by a battery of robustness checks. We found that cross-section stock risk premia are compensated by an increased amount of *EMO* in the market. The pricing of *EMO* is distinct from the idiosyncratic volatility anomaly (Ang et al., 2006; 2009). The findings consistently support that behavioral arousal risk is priced in the asset market. Thus, in an arbitrageurable noise trading market, arbitrageurs and sophisticated investors require higher premia to trade on elevated emotion risk, similar to the recent finding on the return compensation for the flow driven noise trader risk by Huang et al. (2022).

Secondly, we validate the risk attribute of the *EMO* by regressing it with the decomposed risk and mispricing components. Following Birru et al. (2020), we run return decomposition to risk and mispricing factors. The results show that social media emotion intensity and news and social media emotion intensity impose a significant loading on the risk component, but none of the three measures of emotion-related risk has significant effect on the mispricing component. Our finding further supports that a high moment measure of emotions captures the risk premium of stock returns but is uncorrelated with mispricing. However, this finding is contrary to the documented sentiment induced overpricing by previous research (Baker and Wurgler, 2006; Tetlock et al., 2008; Edmans et al., 2022; Obaid and Pukthuanthong, 2022). This sharp contrast also suggests that volatility of emotions is largely orthogonal to sentiment predictors.

Thirdly, we investigate whether the risk source of *EMO* is from informed investors or noise traders. Institutional investors are sometimes referred as “informed” traders who possess superior resources and skills in processing information efficiently (Chen et al., 2000; Puckett and Yan, 2011), while retail investors are like to be noise traders who exhibit strong gambling propensity (Han and Kumar, 2013). We used a stock’s institutional ownership as a proxy for informed investors’ trading activities on this asset. To study how institutional ownership affects stock pricing of the EMO factor, we generate an interaction term between *EMO* and the institutional holdings measures. The result indicates that the pricing of EMO becomes less notable for stocks with a high institutional ownership ratio (informed trading). This suggests that the source of emotion risk is mostly from noise trading instead of informed trading.

Lastly, we have also checked the effect of public relations on EMO and tested the persistence of *EMO* with the interaction of different periods and business cycles. Firm expenses on public relations, such as advertising, can influence multiple stock empirical regularities, such as retail attention, trading volume, stock liquidity, and breadth of ownership (Grullon, Kanatas, and Weston 2004, Frieder and Subrahmanyam 2005, Lou 2014). To examine the effect of advertising on the association of EMO and stock return, we form an interaction term between *EMO* and advertising expenditure scaled by total sales. This result indicates that corporate advertising attracts investor attention to enhance the positive pricing of behavioral arousal risk. Further, we examined the pricing of EMO over subperiods of 1999-2007 and 2008-2017, as well as economic booms and recessions. The evidence supports that the effect of emotion driven noise trading risk has become more pronounced over time. In addition, the finding suggests that the positive effect of EMO on stock returns prevails during economic expansions when arbitrageurs are more active in hedging noise trader risks.

Our paper is related to work that empirically tests the pricing of investor psychology. Examples include Hirshleifer and Shumway (2003), Edmans et al. (2007), Mayew and Venkatachalam (2012), Da et al. (2015), and Edmans et al. (2022) among others. Even though, an ample amount of literature has studied psychology driven mispricing in financial markets. However, there is still a lack of research viewing market participants' emotion as a behavioral risk indicator. Through portfolio analysis, multivariate regression and risk vs. mispricing decomposition, our empirical evidence validates that the behavioral arousal risk is priced in asset risk premia just like fundamental risks. Additionally, this newly learned idiosyncratic behavioral risk effect is distinct from the idiosyncratic volatility anomaly.

A related strand of the literature documents the effect of sentiment on proxies for speculativeness. Brown and Cliff (2004) documented adopted American Association of Individual Investors (AAII) sentiment levels and changes; Baker and Wugler (2006) constructed economic-based sentiment (PCA of common sentiment measures); Tetlock (2007) text mined Wall Street Journal (WSJ) news sentiment; Both Edmans et al. (2022) and Obaid and Pukthuanthong's (2022) apply machine learning algorithm to quantify music mood and photo pessimism. We propose a novel approach to test the volatility of emotions as a behavioral risk indicator in asset pricing, which is one of the first to evaluate high moments of investor sentiment. The cross-validation and decomposition suggest that volatility of emotions is largely orthogonal to sentiment level and change measures.

Our paper also contributes to the behavioral finance literature that to investigate the pricing of noise trading intensity in active asset management. Noise contributes to the financial market liquidity (Black, 1986); however, the passive noise trading hypothesis posits that the amount of noise traders prevents arbitrage activities due to the limit to arbitrage (Shleifer and Vishny, 1997). We offer new empirical insights to study the required risk premium for active asset managers to arbitrage pricing errors in a noise trading market, which has also been supported in Huang et al.'s study (2022) of flow driven noise trader risk.

The remainder of this paper is organized as follows. Section 2 summarizes the literature about investor emotion, idiosyncratic volatility and noise trading. Section 3 introduces the data and how the *EMO* measure is constructed. Section 4 provides empirical results and discussions of *EMO* risk in regressions, portfolio performances, return decomposition, and a battery of robustness checks. Section 5 lists concluded remarks and suggests future research avenues.

2. Literature Review

2.1 Investor emotion

In psychology, emotion is often defined as a complex mental state associated with thoughts, feelings and behaviors. Experimentalists documented that the emotional state of an individual investor influences the individual's risk-taking behavior (Kuhnen and Knutson, 2011) and trading performance (Lo, Repin and Steembarger, 2005)). The Wall Street motto "buy on fear, sell on greed" also indicates that financial professionals understand the importance of market emotions in affecting securities' prices. With the emergence of neurological finance in the last two decades, a few scholars utilized voice analysis and facial recognition to detect investors' or corporate managers' emotions and further study their financial decision making and investment performance. Two published studies, Mayew and Venkatachalam (2012) and Price et al., (2017), adopted the layered voice analysis platform to isolate CEOs' emotional cues from their speeches during the earnings conference calls. The research pairs also tested the stock market reactions to CEOs' emotional cues. Mayew and Venkatachalam (2012) showed that investors react to managers' emotional cues in a pattern that picked up cumulative abnormal returns around the conference calls; those returns extended out six months. Price et al., (2017) found that investors appear to overreact to managers' emotional cues in the conference calls, whereas there is a rapid correction to this short-run overreaction. Another published work, Akansu et al., (2017), utilized a facial recognition system to quantify CEO mood from the interview videos of CEOs of Fortune 500 companies. They (2017) indicated that Anger or disgust motivates a CEO to improve the firm profitability in the subsequent quarter; happiness reduces the CEO's productivity and further cause the profitability to decrease in the following quarter; fear has a significant transient impact contributing to the firm short term performance improvement. Recent empirical evidence supports that news and social media emotions affect both current and short-term future returns in a variety of markets, including commodity, equity and fix income (Shen et. al, 2017, 2021; Griffith et al., 2019).

Most of the investor emotion literature tracks the positive vs. negative valence (sentiment) as affective states in the investors' information processing and decision makings. Investor sentiment research received a large amount of attention from academic research in the last three decades. The mainstream sentiment indicators can be categories in three groups: economic-based sentiment, survey-based sentiment, and media-based sentiment. The traditional economic-based sentiment indices include: closed-end fund discount (Zweig, 1973; Neal and Wheatley, 1998), trading volume (Baker and Stein, 2004), and composite sentiment index based on the first principal component of common sentiment proxies (Baker and Wurgler, 2006; Gao and Suss, 2012). Baker and Wurgler (2006) found that the cross-section of future stock returns is conditional on beginning-of-period proxies for sentiment by constructing economic-based sentiment (PCA of common sentiment measures). The two main survey-based sentiment measurements are: sentiment survey from American Association of Individual Investors (AAII) and sentiment survey from Investor's Intelligence (II) sentiment survey (Brown and Cliff, 2004, 2005). Brown and Cliff (2004) documented that sentiment levels and changes are strongly correlated with contemporaneous market returns by applied survey-based investor sentiment (AAII). Along with the development of computer enabled content analysis, textual sentiments analyses have been applied to algorithmically mine investors' sentiments from news and social media. The most common content analysis methods in textual sentiment analysis are dictionary-based approach and machine learning (Kearney and Liu, 2014). Tetlock (2007) implemented Harvard IV-4 dictionary in GI to run textual analysis in daily news from Wall Street Journal and further suggested that sentiment pessimism imposes downward pressure on market prices followed by a reversion to fundamental. Garcia (2013) in a longitudinal study indicated that the daily news sentiment predicts the following five days' stock returns and this predictive power is more significant during economic recessions. Edmans et al. (2022) introduced a language free music mood index, which goes hand in hand with Obaid and Pukthuanthong's (2022) machine learning applied photo pessimism index. Both music and photo sentiment indices predict market return reversals, consistent with sentiment-induced temporary mispricing.

According to cognitive appraisal theory, different dimensions of emotions affect the investors' perception of risk and their assessment of monetary value (Lerner and Keltner, 2001). The ten commonly studied investor emotions are optimism, joy, love/hate, trust, anger, conflict, gloom, fear, stress and surprise Their theoretical implications and empirical effects have been documented in the earlier behavioral finance literature respectively. Financial optimism is defined as the overestimation of the future financial outcome, so it sometimes causes the investors' overconfidence and the assets' overpricing in the market (Balasuriya et al., 2010). Ciccone (2003) reported that firms with overly optimistic expectations earn lower returns than those with pessimistic expectations. Finance researchers often regard sunshine and temperature as indicators of investors' joy. Hirshleifer and Shumway (2003) confirmed that the stock market performs better during sunny days than during cloudy days. This documented "sunlight effect" attributes to investors' joyful mood to sunshine rather than to long-term value growth. Christiansen et al. (2010) found that females increase the fraction of wealth invested in stocks after marriage (love) and decrease it after divorce (hate), whereas males show the opposite investment behavior. Guiso et al. (2008) provided evidence that the lack of trust is an important factor in explaining the limited stock market participation. Anger is related to the systematic risk of the market. Psychological experiments showed that angry people expressed optimistic risk estimates and risk-seeking choices (Lerner and Keltner,2001). Schneider and Troeger (2006) show that the international conflicts affect the interactions at the main financial markets negatively. The gloomy stage of the market downturn may take years to recover, because investors are more sensitive to the fragile market (Lauricella, 2011)). Azzi and Bird (2005) found that the market boom or gloom state affects the financial analyst's recommendation tendency, where analysts' recommendations favor more high momentum growth stocks during the boom years than during the gloom years. Fear interrupts the market with emotional turmoil, so that further elevates the market uncertainty. The implied volatility indices are often used as proxies for market fear. High levels in the implied volatility indicate that investors are fearful about the market future prospect, so previous research adopted the implied volatility indices (VIX among others) to forecast the forward-looking financial security returns (Esqueda et al., 2015; Rubbaniy et al., 2014). Stress disturbs the market's normal state of functioning. Preis et al. (2012) proposed that the average correlation among the stocks listed on Dow Jones Industrial Average (DJIA) increases with the increase of the market stress, so the benefits of portfolio diversification diminish during the state of the stressful market. Hautsch and Hess (2002) supported that strong magnitude effects of have an impact on volatility in turn to create more uncertainty.

Even though, an ample amount of literature has studied emotion valence driven mispricing in financial markets. However, there is still a lack of research viewing the effect of market participants' emotion arousal. Hasan et al. (2022) provide evidence that stock returns and portfolio performance are affected by the intensity of excitement and anxiety measured by taking the absolute values. In our research, we take the principle component of ten mostly studied emotions, then to propose a volatility measure to construct the arousal of emotions, which is also one of the first few to study high moments of emotions.

2.2 Idiosyncratic volatility

Asset pricing theory suggested that idiosyncratic volatility (IVol), a proxy for idiosyncratic risk, should be priced; however, empirical findings on the pricing of idiosyncratic risk is rather mixed. According to theorists, such as Merton (1987), one expected to see a positive relation between idiosyncratic risk and expected return when investors do not diversify their portfolios. Lehmann (1990) and Malkiel and Xu (1997) provided evidence that idiosyncratic risk is priced in the cross-section of stocks. Campbell et al. (2001) documented a positively increased idiosyncratic volatility during the 1962–1997 period, comparing to the stable market and industry volatilities. Arena et al. (2008) also found time-series evidence of a positive relation between aggregate IVol and momentum returns and suggested this effect as an explanation for the increase of momentum profits. Yang et al. (2020) proposed an information risk measure, abnormal idiosyncratic volatility (AIV), to capture information asymmetry faced by uninformed investors and showed that stocks with high AIV earn larger future returns than stocks with low AIV. However, some other important literature posited an idiosyncratic volatility puzzle, which is contrary to the classical asset pricing of idiosyncratic risks. Ang et al. (2006) documented that monthly stock returns are negatively related to the one-month lagged idiosyncratic volatilities between 1986 and 2000. Jiang et al. (2009) provided further evidence that idiosyncratic volatility is inversely related to future earning shocks. Angat al. (2009) also found similar patterns in the international markets that stocks with past high idiosyncratic volatility had low future average returns across 23 developed markets.

There are numerous explanations for the idiosyncratic volatilities puzzle. Stambaugh et al. (2015) documented that the combination of arbitrage asymmetry with arbitrage risk represented by idiosyncratic volatility (IVol) explains the negative relation between IVol and average return. Caglayan, et al. (2020) found that the stock market turnover has a positive and significant impact on the country-level idiosyncratic volatility, while information disclosure and investor uncertainty avoidance degree are negatively associated with country-level idiosyncratic risk by analyzing the determinants of IVols over 47 developed and emerging countries during the period 1995–2016. Hou and Loh (2016) further showed that investors' lottery preferences and market frictions offered some promise in explaining the idiosyncratic volatility puzzle. Berrada and Hugonnier (2013) constructed a new variable that proxies for the product of the stock's idiosyncratic volatility and the investors' aggregated forecast errors and showed that it explains a significant part of the empirical relation between idiosyncratic volatility and stock returns. In the meanwhile, researchers have raised some critiques on the idiosyncratic volatility puzzle. Bali and Cakici (2008) examined the cross-sectional relation between idiosyncratic volatility and expected stock returns by screening for size, price and liquidity and suggested that no robustly significant relation existed between idiosyncratic volatility and expected returns in the sorted different samples. Additionally, Fu (2009) contended that lagged IVol is not a suitable proxy because of the return reversal and the time-varying property of IVol and showed that expected IVol is significantly and positively related to the contemporaneous monthly stock returns based on conditional IVol from an EGARCH estimate.

Motivated by the recent availability of extensive electronic news databases and the advent of new empirical methods, there has been renewed interest in investigating the impact of financial news on market outcomes for idiosyncratic volatility. DeLisle et al. (2016) examined the relation between idiosyncratic volatility and returns around news announcements and suggested that volatility has a price effect beyond a limit to arbitrage. Bali et al. (2018) posited that volatility shocks could be traced to the unusual firm-level news flow, which temporarily increased the level of investor disagreement about the firm value. Boudoukh et al. (2019) fundamental information in news accounted for 49.6% of overnight idiosyncratic volatility (vs. 12.4% during trading hours.

Engle et al. (2021) proposed econometric specification for firm-specific return volatility decomposition with two components: public information and private processing of public information. They further showed that indicators of public information arrival explain on average 26% of changes in firm-specific return volatility.

Investor psychology, including sentiment and emotion, has also been considered to play an important role in stock market volatility. Gervais and Odean (2001) documented that price volatility could be due to the degree of self-attribution bias and overconfidence. Chang et al. (2008) measured the influence of investor overconfidence on the increased idiosyncratic risk both across stocks and over time. Shi et al. (2016) analyzed the effects of news and its sentiment on the idiosyncratic volatility (IVol) and expected return relation. Qadan (2019) evaluated the role of investor sentiment in explaining the variations in idiosyncratic volatility over time. Further explanations are provided by behavioral researchers. Daniel et al. (2002) suggested that psychological variables limit investors' ability to make value judgments prior to stock tradings. Hirschilerifer (2001) posited that misperceptions are strongest in the idiosyncratic corners of the marketplace. The focus of our study is to measure the behavioral risk from "the idiosyncratic corners of the marketplace" rather than to provide additional behavioral explanations on idiosyncratic volatility phenomena. Thus, we consider idiosyncratic variability of commonly studied emotions manifested in news and social media as a valid behavioral arousal risk proxy.

2.3 Noise Trading

The emotion variability reflects the sum of individual investors' affective arousals towards a specific asset. It is more of an "animal spirit" or "casino instinct" (Loewenstein and Lerner, 2003) of investors in gambling by chances on uncertain outcomes instead of a passive noise trading market in forming information processing bias and security mispricing. Traditionally, a passive noise trading hypothesis postulated that noise traders' risk prevailed in the market eliminates arbitrageurs' activities in correcting security price misvalutions (DeLong et al., 1990). On one hand, noise is necessary to provide financial market liquidity, because there is no noise trading, there will be very little trading in individual assets (Black, 1986). One the other hand, noise trading from irrational investors is also considered as one of the major sources contributing to an inefficient market. Facing the ever-changing finance and media technologies, it becomes a challenge for asset managers to hedge against the increased intensity of noise trading yet to stay participated in the market transactions. Hereby, we hope to explore the effect of behavioral arousal in a proposed active asset management scenario of noise traders in contrast to the passive noise trader market.

Efficient market theory encountered some challenges when it comes to the realistic finance world, such as pricing anomalies – momentum and contrarian, excessive volatility, market crash etc.; therefore, Shleifer and Summers (1990) introduced a noise trader approach to capital markets. Noise traders are those who trade on noise as if it were information. According to a passive noise trader market model, there are two assumptions underpinning the hypothesis. First, a market is made up by rational investors and irrational traders whose sentiments are not fully justified by fundamental news. Second, arbitrage is risky and therefore limited. Noise trading hypothesis posits that large price movements develop from irrational (noise) traders (Cutler et al., 1989; De Long et al., 1990). Additionally, "limit to arbitrage" presumption suggests that arbitrage becomes ineffective in extreme circumstances when prices diverge far from fundamental values (Shleifer and Vishny, 1997). In this case, assets with high idiosyncratic variance may be overpriced, and this overpricing is not eliminated by arbitrage because shorting them is risky, especially for the small size, illiquid and glamour stocks. If noise trading plays as a mispricing factor, hypothetically, the demand shocks from irrational traders pushes prices away from the underlying security values and volatility risk is not proportionately priced. However, in an active market, asset managers are not prevented from engaging arbitraging noise traders' errors as long as the behavioral risk premium is compensated. Therefore, when noise trader risk becomes a risk factor, it takes into account in asset pricing as an idiosyncratic risk in addition to systematic risks.

The impact of noise trading on asset prices is multifaceted indicated by existing literature and models (Black, 1986; Scruggs, 2007), yet the theoretical and empirical evidence on whether the noise trader risk is priced is still rather debatable. Both mispricing and risk components of noise trading coexist and the dominant effect of either one over the other varies considerably among different research contexts. Mispricing formed when the asset prices deviate from fundamental values for long periods of time. Lamont, and Thaler (2003) showed that Internet stocks were priced much too high around 1998–2000 due to overwhelming noises in the market. Tetlock (2006) summarized that securities markets with persistently high noise trade exhibit significant pricing anomalies. Lamont, and Thaler (2003) summarized that Internet stocks were priced much too high around 1998–2000 due to overwhelming noises in the market. In a laboratory experiment, Bloomfield et al. (2009) found that uninformed traders trade against recent price movements to their own detriment that diminishing the ability of market prices to adjust to new information. Risk is derived when rational investors are actively engaging in costly arbitrage so a high premium is required by rational investors. Sias et al. (2001) examined whether noise trader risk is priced in closed-end fund. They demonstrated that the returns on fund shares exhibit more volatilities and a greater mean reversion but not a higher level of compensation than those underlying assets. However, Huang et al. (2022) successfully documented that the noise trader risk is priced and factor premia are higher when mutual funds' flow-driven noise trader risk is more salient. Furthermore, Flynn (2005) suggested that non-diversifiable noise-trader risk increases when the more funds are mispriced; in the meanwhile, this unique risk factor demands a compensatory rate of return by rational investors.

Psychological shocks are "non-fundamental" risks that attributed to investors irrationality that can be useful in modeling noise trading in the financial analysis. Barberis et al. (1998) posited that investors underreact to inadequate pieces of good news, while they overreact to an abundance of good news. Daniel et al. (1998) suggested that investors' overconfidence about private signals and their biased self-attribution contribute to under- and overreactions in the securities market. Hong and Stein (1998) indicated that under- and overreactions arise from the interaction of momentum traders and news watchers. Yu and Yuan (2011) showed that the correlation between the market's expected return and its conditional volatility is positive during low sentiment periods and nearly flat during high-sentiment periods. They argue that the participation of noise traders is higher comparing to rational investors during such periods. Existing literature has documented a variety of affective biases, however, to further explore the risk components of investor emotion in asset pricing is still limited. In our research, we adopt the variability of emotion instead of positive vs. negative sentiment as a measure of noise trading intensity in an active arbitrageur-noise trader market. The assumption is that the rational investors are not prevented from participating in arbitrage activities as the intensity of noise trading changes. Then, based on this active noise trading proposal, the increased cost of arbitrage to noise trading is considered as a behavioral risk factor that need to be priced in such an market. Built on the above premise, the goal of the research is to examine 1. whether idiosyncratic volatility of emotions (EMO) is compensated by asset risk premia; 2. how this EMO risk is different from the mispricing phenomenon; and 3. what is the source of EMO risk - noise trading?.

3. Data and methodology

3.1. Measuring idiosyncratic emotion

In this research, we test the effects of psychological emotion(s) on stock returns. Specifically, we study the effects of ten investor emotions on monthly stock returns: optimism, joy, love/hate, trust, anger, conflict, gloom, fear, stress and surprise. Our stock-specific emotions, market-level emotions and corresponding buzz data come from the Thomson Reuters MarketPsych Indices (TRMI). TRMIs apply lexical analysis to extract news and social media in real-time to convert the volume and variety of professional news and the internet into manageable information flows that incorporate into investment and trading decisions process – quantitative or qualitative. TRMIs are evaluated on three different content sets: news, social media, and the combined content. The data period starts from January 1998 to December 2017. The news sources cover the mainstream news, which includes top international and business news sources, top regional news sources, and leading industry sources (*The New York Times, The Wall Street Journal, Financial Times, etc.*). The social media source includes the internet forum, such as *Seeking Alpha* and finance-specific tweets. This includes generally the top 20% of blogs, microblogs, and other financial social media content.

Since TRMIs are constructed internally as Buzz-weighted averages across various News and Social Media content sources. We can construct custom TRMIs of varying window lengths from Buzz-weighted averages of minutely TRMI data. To be consistent with previous literature, we construct monthly TRMIs using the following method:

For a given company, let $Buzz_0, Buzz_{-1}, \dots, Buzz_{-(N-1)}$, and $TRMI_0, TRMI_{-1}, \dots, TRMI_{-(N-1)}$ represent the corresponding Buzz and TRMI daily data over the trailing N days each month. Then the Buzz-weighted average TRMI over the trailing N-day window length may be explicitly calculated as:

$$(Buzz_0 * \ TRMI_0 + Buzz_{-1} * TRMI_{-1} + \cdots + Buzz_{-(N-1)} * TRMI_{-(N-1)})/(Buzz_0 + Buzz_{-1} + \cdots + Buzz_{-(N-1)}) \quad (1)$$

Our key investor emotion proxies are generated from ten TRMI's emotional indicators, which reflect ten basic emotions: optimism, joy, love/hate, trust, anger, conflict, gloom, fear, stress and surprise. Based on Thomson Reuters' user's guide, Optimism reflects the average score of reference to optimism, net of references to pessimism; Joy reflects the average score of reference to happiness and affection; Love/Hate reflects the average score of reference to love, net of references to hate; Trust reflects the average score of reference to trustworthiness, net of references connoting corruption; Anger reflects the average score of reference to anger and disgust; Conflict reflects the average score of reference to disagreement and swearing net of agreement and conciliation; Gloom reflects the average score of reference gloom and negative future outlook; Fear reflects the average score of reference to fear and anxiety; Stress reflects the average score of reference to distress and danger; Surprise reflects the average score of reference to unexpected events and surprise.

Among our ten emotions, optimism, love/hate, trust and conflict are bipolar indices and the other six indicators are unipolar indices. Based on Thomson Reuters' definition, the bipolar index ranges from -1 to 1. The unipolar index should be in the range from 0 to 1 in most cases. However, it is possible that a negative value shows up because of many negative comments for an asset. According to Thomson Reuters' guide, unipolar indices should be positive over 90% of the time.

Following Ang et al. (2006), we measure idiosyncratic volatility of emotion as the standard deviation of residuals from a regression of monthly stock-specific emotion on the market-level emotion. In order to combine information from those ten emotional indicators while avoiding overfitting, we follow Ludvigson and Ng (2007, 2009) and adopt the principal component analysis (PCA)[4]:

Let $x_t = (x_{1,t}, \dots, x_{10,t})', t = 1, \dots, T$, denote a 10-vector of emotional indicators, where T is the number of observations. And by extracting the latent factors with a reduced dimension, let $\widehat{F}_k$ for $k = 1, \dots, T$ represent a vector comprised of the first principal components of x_t estimated using data up to time k. The first principal component identifies the key co-movements among the ten emotional indicators, while filtering out much of the noise in individual emotion. We then apply a 12-month rolling with one-month iteration regression framework[5] to generate the idiosyncratic

[4] We also apply partial least squares (PLS) of Kelly and Pruitt (2013, 2015) for dimension reduction, and the results still hold.

[5] We also compute idiosyncratic volatilities of emotion from the regression (2) on daily data over each month, and the results still hold.

volatility of emotion based on the first principal component $\hat{F}_{i,t}$ estimated from $x_{i,t}$ for stock-level ($\widehat{STK}_{i,t}$) and market-level[6] ($\widehat{MKT}_t$):

$$\widehat{STK}_{i,t} = \alpha_i + \beta_i * \widehat{MKT}_t + \epsilon_{i,t} \tag{2}$$

Then, Following Ang et al. (2006), we define idiosyncratic volatility of emotion ($EMO_{i,t}$) as the standard deviation of residuals $\epsilon_{i,t}$ in Eq. (2). Given that the TRMIs are evaluated on three different content sets: news, social media, and the combined content, we can generate the idiosyncratic volatility of emotion for the following types:

1. EMO^N: the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions derived from the mainstream news, which include top international and business news sources, top regional news sources, and leading industry sources.

2. EMO^S: the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions derived from the internet forum and finance-specific tweets.

3. EMO^{NS}: the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions derived from the combined content.

3.2 Data sample and summary statistics

The data sources used in our analysis are described in this section. We obtain stock and market returns data from Center for Research in Securities Prices (CRSP) and firm fundamentals data from Compustat. Data on institutional holdings are obtained from Thomson Reuters. Data on business cycle are from National Bureau of Economic Research (NBER). Data for generating mispricing

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[6] We use the 10 emotions from SP500 index oriented TRMIs to compute the market-level idiosyncratic volatility of emotion.

and risk factor returns are from the authors' websites[7]. Our final sample includes all common stocks listed on the NYSE, Amex, and Nasdaq that are covered in CRSP and Compustat. We exclude stocks with prices below one dollar at the end of the previous month. Our final sample consists of 951,047 firm-month observations spanning from January 1998 to December 2017.

Table 1 reports the descriptive statistics of our sample. EMO_{NS}, EMO_N, and EMO_S are our key measures of investor emotion risk, defined as $\sqrt{var(\epsilon_{i,t})}$ in Eq. (2). The average raw return (*Ret*) is 1% per month with a standard deviation of 17.4%. *IVOL* is the standard deviation of daily residuals based on the Fama and French (1993) three-factors model during the previous month following Ang et al. (2006). *Beta* is the market beta of the stock with respect to the CRSP value-weighted index estimated following Fama and French (1992). *Size* is the market capitalization at each month. *BM* is the book-to-market ratio. *Amihud* is the illiquidity measure in Amihud (2002).

[INSERT TABLE 1]

In order to further show the temporal changes of the EMO index, the average annual buzz of EMO and the total number of companies covered by the EMO index during the sample period are depicted in Figure 1. The buzz of emotion represents a sum of entity-specific words and phrases used in the TRMI emotion index computations. We find that the buzz of emotion and the number of firms covered show an upward trend year by year and reach the peak after 2012. In 2012, social media hit new heights this year. Facebook reached 1 billion users. Pinterest saw explosive growth with 17.8 million site visits. LinkedIn touting a 13 percent increase in user activity from the previous year. And for Twitter, there are more than 100 million users post 340 million tweets a day by 2012. In the meanwhile, news consumption is increasing with the spread of mobile technology, enhancing the appeal of traditional news brands and even facilitating the reading of long-form news.

[7] FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019).

[INSERT FIGURE 1]

We also compare the stock return and idiosyncratic emotion for EMO-sorted portfolios. Figure 2 shows that the stock return increase with the level of idiosyncratic emotion. Stocks with more positive idiosyncratic emotion have higher return.

[INSERT FIGURE 2]

4. Idiosyncratic Volatility of Emotions and Stock Returns

In this section, we examine whether our measure of idiosyncratic volatility of emotions (EMO) is being priced into stock returns. First, we employ both the portfolio approach and multivariate analyses to examine the relation between EMO and stock returns. We also use alternative regression techniques to examine the robustness of our baseline results. Second, we investigate the explanatory power of *EMO* on the mispricing and risk components by decomposing returns. Third, we assess how institutional ownership and corporate advertising influence the association between *EMO* and stock returns. Last, we test how the pricing effect of *EMO* varies with different time periods and business cycles.

4.1 The effect of Idiosyncratic volatility of emotion on returns

Portfolio approach: To evaluate the potential effect of idiosyncratic volatility of emotions (*EMO*) on future stock returns, we construct monthly equal-weighted portfolios sorted by *EMO*. The results are presented in Table 2. Panel A shows the average CAPM, Fama-French three factor, and Carhart four-factor risk-adjusted alphas of single-sorted quintile portfolios sorted monthly by prior-month's *EMO*. For all the three risk-adjusted return measures, there exists an increasing relationship between *EMO* and future stock returns. In particular, the relationship is monotonically increasing across all quintiles for the three excess return measures. The differences in risk-adjusted returns between the High and Low *EMO* quintiles are all positive and significant at the 1% level.

More importantly, the return spreads between the High- and Low- *EMO* quintiles are economically significant. A trading strategy consisting of a long position in a High-*EMO* quintile and a short position in a Low-*EMO* quintile generates a 5.30%, 5.28%, 5.13% annualized CAPM, Fama-French three factor, and Carhart four-factor risk-adjusted returns, respectively.

[INSERT TABLE 2]

It is possible that the positive risk premium of *EMO* could be simply a manifestation of return effects related to certain firm characteristics such as firm size and book-to-market ratio. To address this potential concern, we sort sample firms into two portfolios based on prior-month's market capitalization and book-to-market ratio, respectively, and then sort each of the two portfolios into quintiles based on *EMO*. Panel B reports the Carhart four-factor risk-adjusted alphas of quintile portfolios for both small and large firms, and for firms with high and low B/M ratio. The results show that the risk-adjusted return spread between High- and Low- *EMO* quintiles are statistically significant for both *Size* portfolios and for both *B/M* portfolios. Especially, the return spread is more notable in small firms and firms with high B/M ratio. For example, the long High-*EMO* and short Low-*EMO* trading strategy yields a 6.24% annualized risk-adjusted return for small firms while a 4.73% annualized return for large firms. Thus, the positive relationship between *EMO* and future stock returns is not driven by firm size or book-to-market ratio.

Multivariate analysis: The portfolio results provide preliminary evidence that the idiosyncratic volatility of emotions has a positive effect on future stock returns monthly returns. In this subsection, we perform multivariate panel regressions to examine the pricing effect of investor emotions. Our regression framework is as following:

$$R_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + \epsilon_{i,t} \qquad (3)$$

where $R_{i,t}$ is measured as the raw monthly stock return ($RET_{i,t)}$ or the excess monthly return ($DGTW_{i,t}$)calculated following Daniel et al. (1997) for firm *i* in month *t*. $EMO_{i,t-1}^{NS}$, $EMO_{i,t-1}^{S}$, and $EMO_{i,t-1}^{N}$ are the idiosyncratic volatility of emotions generated using TRMIs ten emotions.

$Control_{i,t-1}$ are control variables including market beta (*Beta*), market capitalization (*Size*), the book-to-market ratio (*B/M*), illiquidity ratio (*Amihud*) from Amihud (2002), past month stock return (Ret_{t-1}), and idiosyncratic volatility (*IVOL*) from Ang et al. (2006). The regression estimates are reported in Table 3.

[INSERT TABLE 3]

Several interesting results are revealed in Table 3. First, $EMO_{i,t-1}^{NS}$ has a positive and significant effect on future stock returns. It has a coefficient of 0.006 (*t-statistic*=2.50) and 0.006 (*t-statistic*=2.75) in models (1) and (7) when *RET* and *DGTW* serve as the dependent variable, respectively. Second, the effect of $EMO_{i,t-1}^{S}$ is significant or marginally significant while the effect of $EMO_{i,t-1}^{N}$ is not significant. This suggests that the idiosyncratic volatility of emotion based on mainstream news does not have pricing effect, probably because the content of mainstream news has already been priced into the stock performance and the emotion implied by such news has no additional effect on stock returns. Third, our results are not affected by including $IVOL$ as an additional control variable. Ang et al. (2006) show that stocks with high idiosyncratic volatility have low average returns. To ensure the pricing effect of EMO is not a manifestation of $IVOL$, we control for $IVOL$ in models 4 to 6 and 10 to 12. As shown in these models, EMO^{NS} and EMO^{s} have an independent pricing effect even after controlling for $IVOL$.

Overall, our multivariate analyses provide strong evidence that the risk associated with investor emotions has significant pricing implications and its pricing effect is not affected by firm characteristics, stock liquidity level, past returns, and idiosyncratic volatility risk.

4.2 Alternative regression techniques

In this section, we use a battery of alternative regression techniques to examine the robustness of the pricing effect of *EMO*. Specifically, we examine whether our results are robust to the firm and year fixed-effects, Fama-Macbeth regressions, firm-year clustered standard errors, and three lagged Newey-West tests.

We use firm fixed effects model to control for the unobserved sources of firm heterogeneity and year fixed effects model to capture unobserved firm-invariant heterogeneity. The results in Table 4 show that the coefficients of EMO^{NS} and EMO^{s} are positive and significant across all the models. This within-firm test confirms that the relation between the idiosyncratic volatility of emotion and stock returns is unlikely to be driven by the differences across firms or whatever events over time.

[INSERT TABLE 4]

To correct for cross-sectional correlation, we employ the Fama-Macbeth regressions. That is, we follow Fama and Macbeth (1973) and estimate Equation (3) cross sectionally each month. The cross-sectional return determinants include *Beta*, *Size*, *B/M*, *Amihud*, $Ret_{t-1,}$ and *IVOL*. Time-series averages of the coefficient estimates are reported in columns 1 to 3 of Table 4. To address the potential serial correlation problem in our panel data, we cluster standard errors at firm-year level, instead of using ** standard errors, in columns 4 to 6 and three lagged Newey-West tests in columns 7 to 9. The results based on these alternative regression techniques confirm our finding regarding the positive relation between behavioral arousal risk and future stock returns

4.3 Decomposition of stock returns

In this section, we follow Birru et al. (2020) to investigate the role of investor emotion-related risk in the return generating process. Birru et al. (2020) argue that stock returns can be decomposed into two components: mispricing component and risk component. The former is due to systematic mispricing that captures the anomalies predicted by behavioral theories and the latter is purged of systematic mispricing and reflects non-behavioral forces, thus showing cross-sectional return relations consistent with standard asset pricing models. They also predict that the mispricing component disproportionally reflects sentiment-induced mispricing whereas the risk component disproportionally reflects risk. Consistent with their prediction, they present evidence that sentiment helps identify variation in mispricing but exhibits little or no predictive power for the risk component. Given the positive effect of our measure of emotion-related risk on future stock returns, we expect it has some predictive ability for the risk component.

To compute the mispricing component and the risk component, we estimate the following specification:

$$R_{i,t} = \alpha_{i,j} + \beta_{i,j} * X_{j,t} + \varepsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ is the DGTW excess return of firm i in month t and $\beta_{i,j}$ and $X_{j,t}$ are vectors of loadings and mispricing factors, respectively, corresponding to factor model j. We define the mispricing component as the sum of the product of the estimated loadings and factors as indicated by $\beta_{i,j} * X_{j,t}$, and the risk component as the remaining return, $\alpha_{i,j} + \varepsilon_{i,t}$. This decomposition thus generates an explained component of returns, representing mispricing, and an unexplained component of returns, representing risk.

Following Birru et al. (2020), we employ three sets of behavioral factor models. We decompose the stock return with respect to the monthly mispricing factors FIN, PEAD, MGMT, PERF, and QMJ. More specifically, Daniel et al. (2020) propose two factors, FIN and PEAD, that are expected to capture commonality in mispricing. They argue that FIN is a short-horizon behavioral factor while PEAD is a long-horizon one. Stambaugh and Yuan (2017) introduce two factors, PERF and MGMT, that can be viewed as short-term and long-term mispricing factors, respectively, capturing common covariance in mispricing by combining different clusters of anomalies. Asness et al. (2019) propose a quality-minus-junk (QMJ) factor that is related to analysts' expectational errors and captures time-variation in systematic mispricing to some extent. We collect these factors from the authors' websites. We retrieve the mispricing component and risk component from Equation (4) and then estimate the following two models:

$$RISK_{i,t} = a + b_1 EMO^{NS}_{i,t-1} + b_2 EMO^{S}_{i,t-1} + b_3 EMO^{N}_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t} \tag{5}$$

$$MP_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + \epsilon_{i,t} \quad (6)$$

where *RISK* is the risk components of return and *MP* is the mispricing components that are generated by estimating Equation (4). The results are presented in Tables 6 and 7.

[INSERT TABLE 6 & 7]

Table 6 reports the effect of *EMO* on the risk component of DGTW excess returns. The results show that the coefficients of EMO^{NS} and EMO^{s} are positive and significant at 1% or 5% level across all three mispricing factor models, suggesting that emotion-related risk has a significant loading on the risk component. In contrast, EMO^{N} has no significant effect on the risk component, which corresponds to the result in Table 3 that EMO^{N} has no significant effect on stock returns. Table 7 reports the effect of EMO on the mispricing component. The results indicate that none of the three measures of emotion-related risk has significant effect on the mispricing component, indicating emotion-related risk has no predictive power for the systematic mispricing of returns.

In sum, the results from Table 6 together with our main finding of the positive pricing effect of the emotion-related risk reinforces that the behavioral arousal risk is indeed an important risk factor in the return-generating process.

4.4 Institutional ownership

In this section, we examine whether the relation between *EMO* and future stock returns is affected by institutional ownership. Institutional investors are sometimes referred as “informed” traders and their trading predicts the occurrence of news announcements, the sentiment of the news, and the stock market reaction on news announcement days (Hendershott et al., 2015). Compared to individual investors, institutional investors are more sophisticated and more resourceful and skillful in collecting and analyzing information. As a result, they exhibit superior stock-picking skills and trading performance (Chen et al., 2000; Puckett and Yan, 2011). On the other hand, stocks with high retail trading proportion have strong lottery features and they attract retail investors with strong gambling propensity. Han and Kumar (2013) posited that stocks with high idiosyncratic volatility and skewness or lower prices are predominately held and actively traded by retail investors, while institutional investors underweight those stocks. Therefore, we expect that a stock's institutional ownership may affect the pricing impact of the idiosyncratic volatility of emotions.

We obtain the institutional ownership information from Thomson-Reuters 13F data and construct three variables to measure the characteristics of institutional holdings. Institutional ownership ratio (*IO*) is total institutional ownership divided by total shares outstanding at the end of a quarter. Institutional concentration (*IC*) is computed as the Herfindahl-Hirschman Index of all institutional holdings of a particular security. The higher the value of *IC*, the more concentrated a stock's institutional ownership structure. Institutional Breadth (*IB*) simply represents the number of institutional investors holding at least 5% of total shares of the stock during the quarter. To examine the possible effect of institutional investors on the relation between *EMO* and future stock returns, we create an interaction term between *EMO* measures and the three measures of institutional holdings. The regression results are presented in Table 8.

[INSERT TABLE 8]

The results show that the association between emotion arousal risk and future stock returns is less notable for stocks with higher institutional ownership, less concentrated institutional ownership structure, and more institutional investors. For example, $EMO^{NS} * IO$, EMO^{S}*IO, and EMO^{N}*IO have a negative and significant coefficient of -0.038 (*t-statistic*=-2.08), -0.052 (*t-statistic*=-2.41), and -0.066 (*t-statistic*=-2.33). The coefficients of interaction terms with *IB* are negative but not statistically significant except that of EMO^{S}*IB. On the other hand, the coefficients of the interaction terms with IC are all negative, with that of EMO^{S}*IC being statistically significant. The results suggest that higher institutional ownership, less concentrated ownership structure, and more institutional investors can reduce the pricing effect of emotion-related information risk, which is consistent with the view that such traits of institutional ownership structure help relieve short-sale constraints and promote the ability of arbitrageurs to take short positions and then facilitate the process of price recovery (Prado et al., 2016). It is also noted that EMO^{N}*IO has the largest coefficient among the three interaction terms, indicating that institutional investors are more effective in mitigating the pricing effect of news media related emotion risk than that of social media related emotion risk.

The *EMO* measures per se still have positive and significant coefficients. As a matter of fact, their independent effect become stronger after incorporating institutional ownership. Compared with our baseline results in Table 3, $EMO^{NS}$and EMO^{S} have larger and more significant loadings on future stock returns. For example, the coefficients of EMO^{NS} and EMO^{S} are 0.007 (*t-statistic*=3.08) and 0.004 (*t-statistic*=1.67) in columns 10 and 11 of Table 3, respectively, whereas they are 0.014 (*t-statistic*=4.73) and 0.015 (*t-statistic*=4.08) in columns 1 and 2 of Table 8, respectively. As for EMO^{N}, it is insignificant in column 12 of Table 2 but has a positive and marginally significant coefficient in column 3 of Table 8. Thus, these results reveal that after accounting for the effect of institutional holdings, the positive effect of emotion-related information risk on future stock returns is more pronounced.

Taken together, Table 8 provides evidence that institutional ownership can shape the pricing effect of behavioral arousal risk. High level of institutional ownership, less concentrated ownership structure, and more institutions may mitigate the positive association between the idiosyncratic volatility of emotions and future stock returns.

To further confirm whether the source of EMO risk is informed trading or noise trading, we perform a 2SLS regression model with retail ownership as the instrumental variable. Following Iselin et al. (2022), $Retail\%$ is the total percentage of retail ownership of the firm. We compute $Retail\%$ by adding total institutional ownership and total insider ownership and assuming the remaining ownership is composed of retail owners.

$$Retail\% = 1 - (Inst\% + Insider\%) \qquad (7)$$

Where $Inst\%$ is measured using the Thomson 13F database and $Insider\%$ is measured using the Execucomp database. The first-stage coefficient of $Retail\%$ in column (1) of Table 9 is -0.017 and significant at the 1% level, which confirms retail ownership is relevant to our idiosyncratic emotion index. Column 2 of Table 9 indicates that the predicted idiosyncratic emotion index coefficient is 0.461, positive and significant at the 1% level. In Columns (3) and (4), we run the panel regression of the interaction term of the EMO index with the deciles obtained based on $Retail\%$ sorting. The positive and significant coefficient of interaction term indicate the possibility of noise trading request more emotional risk premium. Overall, the results indicate that retail ownership is highly correlated with our idiosyncratic emotion index and stocks with higher retail ownership will have more emotion arousal risk premium.

[INSERT TABLE 9]

4.5 Advertising expenditure

This section investigates the possible effect of a firm's advertising policy on the pricing effect of the emotion-related risk. Advertising can promote a firm's public image and have ripple effects on trading in stock markets. Marketing expenditures are positively associated with retail attention, trading volume, stock liquidity, and breadth of ownership (Grullon, Kanatas, and Weston 2004, Frieder and Subrahmanyam 2005, Lou 2014). More recently, using more refined advertising data, Madsen and Niessner (2019) find that both retail attention and trading volume rise on days with newspaper ad, and Liaukonyte and Zaldokas (2020) show that TV ads trigger retail attention and larger trading volume driven primarily by retail investors. Fang, Madsen and Shao (2022) document that advertising not only increases retail trading but also increases retail trading volatility, which in turn amplifies stock price volatility. Informed trading intensity increases as well since informed stock and option traders strategically trade to take advantage of increases in noise trading.

To examine how a firm's advertising affects the pricing effect of idiosyncratic volatility of emotions, we create an interaction term of *EMO* ADV/SALE,* where *ADV/SALE* is a firm's advertising expenditure scaled by total sales. We include the interaction term in our baseline regression model, Equation (3), and the estimation results are presented in Table 10. After accounting for the effect of firm advertising, $EMO^{NS}$and EMO^{S} still have positive and significant relation with stock returns. The interaction terms, $EMO^{NS} * ADV/SALE$ and $EMO^{S} * ADV/SALE$, carry a positive and significant loading on suture excess returns. This result indicates that corporate advertising expenditure increases the positive pricing effect of behavioral arousal risk, probably because advertising attracts investor attention, especially retail attention.

[INSERT TABLE 10]

4.6 Persistence of idiosyncratic volatility of emotion

Our measures of emotion risk are constructed based on investor emotion indicators extracted from news and social media. The evolution of social media as a sociological and commercial force has been fueled by advances in digital technology. According to the 2019 report on social media use by Pew Research Center, 72% of American adults use some form of social media. That share was 50% in 2011 and only 5% back to 2005, the year after Facebook went live. Given the rapid growth of social media in less than a generation, we expect the effect of emotion related information risk might have become more notable over time.

To examine the behavioral arousal risk over time, we split our sample period into two subperiods, 1999-2007 and 2008-2017, and estimate our baseline regression model for each subperiod. The results in Table 11 indicate that, as expected, the effect of emotion-related information risk has become more pronounced over time. The coefficient of EMO^{NS} is 0.008 (t-statistic=1.94) in the early period, which is marginally significant, and 0.012 (t-statistic=3.62) in the later period. The coefficient of EMO^{S} is not statistically significant in the early period but it is positive and significant at 1% level in the later period. By contrast, EMO^N is marginally significant in the first period but lose significance in the second period, probably because of the decline of news media and the rise of social media.

[INSERT TABLE 11]

Moreover, investor emotion risk could vary over different phases of the business cycle as investors could become emotional with the ups and downs of the economy. (Beaudry et. al, 2012) To capture the possible influence of economic conditions on the effect of emotion arousal risk, we classify our sample period into recession and expansion periods based on NBER committee's recession-indicator variables. Then we estimate Equation (3) for each period and present the results in Table 12. Interestingly, we find that the positive effect of EMO^{NS} and EMO^S on future stock returns is significant in expansions but not recessions. This finding is somewhat contradictory to Yu and Yuan (2011), in which volatility risk is compensated during low sentiment periods but not high-sentiment periods. Our explanation is that behavioral arousal risk is more properly arbitraged during expansions when rational investors are more active.

[INSERT TABLE 12]

Our emotions-based measure is different from established sentiment measures. We compare our idiosyncratic emotion index with the following measures: macro uncertainty measure (VIX), economic policy uncertainty index (Baker, Bloom, and Davis, 2016, EPU), investor sentiment (Baker and Wurgler, 2006, SENT), and University of Michigan's Consumer Confidence Index. Panel A of Table 13 presents the correlations between our idiosyncratic emotion index and other measures. We observe that our measure has very low correlation with all alternative measures. Meanwhile, as shown in Panel B of Table 13, our emotion index still exhibits additional explanatory power for future returns after adding these sentiment measures to the main regression model.

[INSERT TABLE 13]

5. Conclusion

A burgeoning growth of behavioral finance literature documented sentiment related noise trading risk and mispricing. Behavioral experimentalists believe that emotion influences investors' monetary evaluation and risk perception. Thus, market psychology could also serve as a source of behavioral risk. This study is motivated to introduce a novel idiosyncratic volatility of emotions (EMO) as a behavioral arousal risk reflecting the casino instinct (Loewenstein and Lerner, 2003) in gambling on uncertain outcomes and to empirically explore whether emotion risk is priced into cross-section stock risk premia.

The passive noise trading hypothesis is only valid when two assumptions are complied by: first, "non fundamental" shocks press prices away from security value; second, there is a limit to arbitrage (Shleifer and Vishny, 1997). To further explain, investor sentiment drives a high participation of noise traders but eliminate the number of rational investors being active in the market (Zweig, 1973). In this designed research, we propose an active arbitrageur-noise trader market that the intensity of noise trading, measured by idiosyncratic volatility of emotions (EMO), does not prevent asset management from actively hedging against behavioral risks. Thus, we relaxed the second assumption - the market level limit for arbitrage. As the individuals' noise trading intensity increases, the rational investors still actively participate in market activities, but they require a higher compensation for bearing more arbitrage costs. The arbitragaguerable noise trading have also been empirically tested by Huang et al. (2022), in which they show that flow-induced noise trading is not merely a temporary demand shock, but also an important source of risk priced by arbitrageurs.

Through our empirical analyses, we documented consistent evidence to support that idiosyncratic volatility of emotions (EMO) is compensated by cross-section stock risk premia. A one standard deviation increase in EMO is associated with about 7.20% annualized excess return growth. We also provide evidence that the *EMO* sorted portfolio earns a positive annualized alpha about 5.30%. The EMO risk pattern applies to media covered large size companies, which is different from the sentiment related mispricing restricted to difficult to arbitrage, small firms (Baker and Wurgler, 2006). Additionally, our documented pricing of EMO is distinct from the idiosyncratic volatility anomaly (Ang et al., 2006; 2009).

We also show that higher moment of investor emotions captures the risk premium of stock returns but is uncorrelated with mispricing by regressing EMO with decomposed risk and mispricing components (Birru et al., 2020). Furthermore, our research suggests that the source of behavioral arousal risk may be from noise trading instead of informed trading, because those firms with high institutional ownership (informed trader) show less effect of emotion risk pricing.

Our research evidence contributes to the investor psychology literature in three important ways. First, we offer the first study to support the role of non-fundamental demand emotion risk on asset prices. Secondly, the empirical evidence support that cross-section stock risk premia is required to compensate behavioral arousal risk. Thirdly, our idiosyncratic volatility of emotions (EMO) measure is the first to evaluate the higher moment of sentiment in asset pricing.

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Table 1 Descriptive statistics of variables

This table presents the descriptive statistics of variables involved in this study. The sample period is from January 1998 to December 2017. The sample consists of all CRSP common stocks with share prices of at least $1 at the end of the previous month. The summary statistics include mean value (Mean), standard deviation (Stdev), total number of firm-month observations (N), 1st percentile, 25th percentile, 50th percentile, 75th percentile, 90th percentile and 99th percentile. Ret is the raw CRSP monthly return. Idiosyncratic volatility (IVOL) is the standard deviation of residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) factors following Ang et al. (2006). Beta is the regression coefficient of the past three years of monthly returns on market returns. Size and B/M are measured as in Fama and French (2006). Amihud is the illiquidity measure in Amihud (2002). EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content.

VARIABLE	N	MEAN	STDEV	1%	10%	25%	MEDIAN	75%	90%	99%
Ret	951,047	0.010	0.174	-0.408	-0.156	-0.065	0.003	0.071	0.167	0.557
IVOL	950,930	0.030	0.027	0.005	0.009	0.014	0.022	0.036	0.057	0.122
Beta	945,988	1.191	19.421	-1.245	0.080	0.474	0.996	1.631	2.443	5.038
Size	951,047	3634	18071	5.83	27.18	78.78	327	1457	5722	65608
B/M	951,047	0.742	15.942	0.032	0.160	0.309	0.554	0.890	1.339	3.337
Amihud	950,952	2.279	69.064	0.000	0.000	0.001	0.016	0.247	2.397	48.502
EMO_{NS}	155,304	1.009	0.542	0.125	0.447	0.652	0.915	1.253	1.666	2.873
EMO_N	56,943	0.982	0.551	0.080	0.405	0.624	0.890	1.224	1.631	2.848
EMO_S	123,583	1.041	0.567	0.136	0.450	0.659	0.941	1.307	1.743	2.961

Figure 1 The Annual Change in Average Buzz of Emotion and the Number of Firms Covered by the Emotion Index
This figure depicts the average annual buzz of emotion and the total number of companies covered by the emotion index in this study. The sample period is from January 1998 to December 2017. The sample consists of all CRSP common stocks with share prices of at least $1 at the end of the previous month. The buzz of emotion represents a sum of entity-specific words and phrases used in the TRMI emotion index computations.

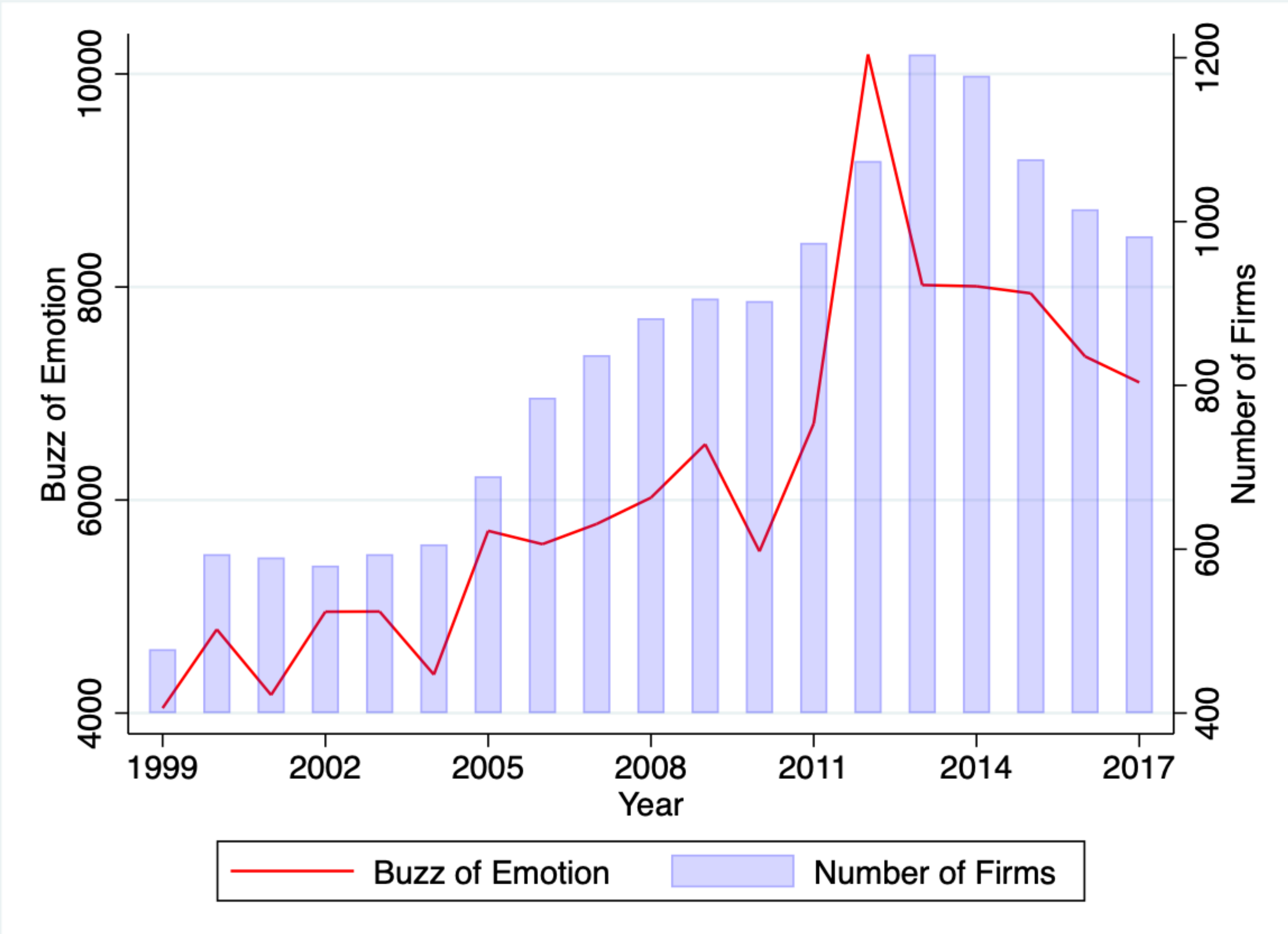

Figure 2 The Average Idiosyncratic Emotion and Stock Return
This figure depicts the average idiosyncratic emotion and stock return of ten portfolios ranked by the idiosyncratic emotion each month. The idiosyncratic emotion represents the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from news and social media content. Ret is the raw CRSP monthly return. The sample period is from January 1998 to December 2017.

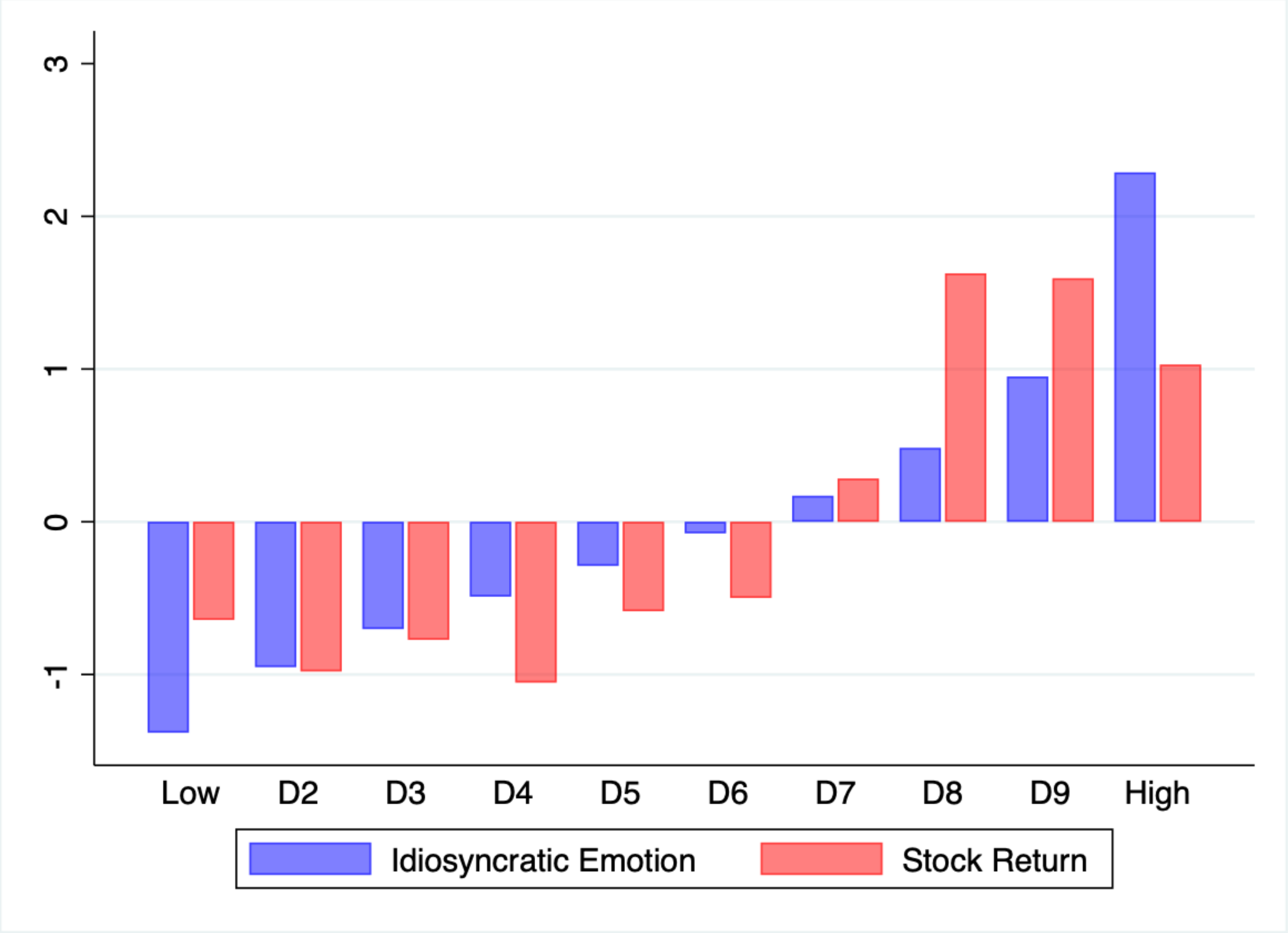

Table 2 Monthly risk-adjusted portfolio alphas of idiosyncratic emotion portfolios

This table reports the CAPM alphas, Fama-French three-factor alphas, and Carhart four-factor alphas of stock portfolios single-sorted on the prior-month's idiosyncratic emotion (EMO) in Panel A. Panel B reports the Carhart four-factor alphas of portfolios double-sorted first by the prior-month's Size or B/M and then by prior-month's EMO. The differences in alphas between the high and the low portfolios are also reported, along with t-statistics in parentheses. Monthly returns and alphas are reported in percentages. The t-statistics reported in parentheses are based on Newey–West standard errors. The sample period is from Jan 1999 to December 2017.

Panel A: Single sorted portfolios, sort by *EMO*			
Portfolios	CAPM alpha	FF3 alpha	Carhart alpha
Low	-0.065	-0.214	-0.180
2	0.090	-0.044	-0.004
3	0.157	0.018	0.039
4	0.290	0.146	0.175
High	0.366	0.216	0.238
High-Low	0.431	0.430	0.418
	(3.78)	(3.83)	(3.75)

Panel B: Double sorted portfolios, sort by *Size* or *B/M*, then *EMO*				
Portfolios	Low *Size*	High *Size*	Low *B/M*	High *B/M*
Low	-0.370	-0.054	-0.060	-0.335
2	-0.194	0.245	0.125	-0.150
3	-0.084	0.201	0.168	0.050
4	-0.141	0.396	0.204	0.046
High	0.136	0.333	0.303	0.183
High-Low	0.506	0.386	0.363	0.518
	(2.93)	(3.61)	(2.64)	(3.29)

Table 3 The effect of idiosyncratic volatility and idiosyncratic emotion on return

This table provides the panel regression results with control variables in the following model.

$$R_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where Ret is the raw CRSP monthly return, DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. Idiosyncratic volatility (IVOL) is the standard deviation of residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) factors following Ang et al. (2006). Beta is the regression coefficient of the past three years of monthly returns on market returns. Size and B/M are measured as in Fama and French (2006). Amihud is the illiquidity measure in Amihud (2002). The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
				RET						DGTW		
EMO_{t-1}^{NS}	0.006**			0.006***			0.006***			0.007***		
	(2.50)			(2.87)			(2.75)			(3.08)		
EMO_{t-1}^{S}		0.005*			0.006**			0.003			0.004*	
		(1.90)			(2.32)			(1.28)			(1.67)	
EMO_{t-1}^{N}			-0.002			-0.002			0.001			0.001
			(-0.63)			(-0.63)			(0.27)			(0.27)
$IVOL_{t-1}$				0.025***	0.023***	-0.023***				0.029***	0.026***	-0.011**
				(7.47)	(6.03)	(-4.16)				(8.73)	(6.96)	(-2.00)
Beta	0.010***	0.017**	0.010***	0.010***	0.016**	0.010***	0.041	-0.018	0.206***	-0.021	-0.071	0.228***
	(2.99)	(2.35)	(3.48)	(2.87)	(2.16)	(3.53)	(1.04)	(-0.42)	(3.22)	(-0.54)	(-1.61)	(3.51)
Size	-0.004***	-0.004***	-0.002**	-0.002**	-0.002*	-0.003***	-0.001	-0.001	0.000	0.001	0.000	-0.000
	(-3.68)	(-3.34)	(-2.57)	(-2.17)	(-1.94)	(-3.33)	(-0.86)	(-1.31)	(0.20)	(0.58)	(0.04)	(-0.14)
B/M	0.054***	0.051***	0.492***	0.052***	0.049***	0.529***	0.374***	0.410***	0.227***	0.330***	0.371***	0.243***
	(4.59)	(4.08)	(6.92)	(4.40)	(3.94)	(7.38)	(7.71)	(7.60)	(3.31)	(6.79)	(6.85)	(3.52)
Ret_{t-1}	0.011***	0.011***	0.011***	0.009***	0.008***	0.011***	-0.012***	-0.014***	-0.001	-0.015***	-0.016***	-0.001
	(4.65)	(3.94)	(2.72)	(3.73)	(3.12)	(2.80)	(-5.14)	(-5.32)	(-0.34)	(-6.10)	(-6.15)	(-0.31)
Amihud	0.503***	1.036***	-1.314	0.436**	0.917***	-1.064	0.281	0.664**	-2.379**	0.209	0.532*	-2.259*
	(2.78)	(3.59)	(-1.04)	(2.41)	(3.17)	(-0.84)	(1.60)	(2.31)	(-1.99)	(1.18)	(1.85)	(-1.89)
Constant	0.037***	0.061***	-0.045	0.038***	0.058***	-0.042	0.034***	0.055***	-0.102*	0.037***	0.054***	-0.101*
	(4.30)	(4.52)	(-0.78)	(4.48)	(4.33)	(-0.72)	(4.10)	(4.14)	(-1.85)	(4.43)	(4.00)	(-1.82)
Observations	153,243	122,035	56,135	153,242	122,034	56,135	149,107	118,629	54,870	149,106	118,628	54,870
R-squared	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.001

Table 4 The effect of idiosyncratic volatility and idiosyncratic emotion on return with fixed effects

This table provides the panel regression results with control variables and fixed effects in the following model.

$$R_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where Ret is the raw CRSP monthly return, DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. Idiosyncratic volatility (IVOL) is the standard deviation of residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) factors following Ang et al. (2006). Beta is the regression coefficient of the past three years of monthly returns on market returns. Size and B/M are measured as in Fama and French (2006). Amihud is the illiquidity measure in Amihud (2002). The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	RET						DGTW					
EMO_{t-1}^{NS}	0.008***			0.011***			0.010***			0.010***		
	(3.20)			(4.27)			(4.20)			(4.22)		
EMO_{t-1}^{S}		0.010***			0.010***			0.009***			0.010***	
		(3.34)			(3.20)			(3.04)			(3.26)	
EMO_{t-1}^{N}			-0.003			0.002			-0.001			-0.000
			(-0.74)			(0.59)			(-0.16)			(-0.04)
$IVOL_{t-1}$	0.044***	0.042***	-0.008	0.058***	0.055***	0.020***	0.042***	0.039***	0.008	0.037***	0.033***	0.012*
	(11.61)	(9.88)	(-1.18)	(14.45)	(12.09)	(2.93)	(11.39)	(9.32)	(1.21)	(9.33)	(7.40)	(1.77)
Beta	0.010***	0.014*	0.010***	0.010***	0.012*	0.010***	-0.020	-0.059	0.320***	-0.040	-0.082	0.300***
	(2.89)	(1.85)	(3.60)	(2.86)	(1.71)	(3.59)	(-0.38)	(-0.98)	(3.31)	(-0.75)	(-1.36)	(3.08)
Size	-0.018***	-0.018***	-0.010***	-0.015***	-0.014***	-0.010***	-0.012***	-0.012***	-0.008***	-0.010***	-0.009***	-0.008***
	(-7.74)	(-7.11)	(-5.22)	(-6.16)	(-5.47)	(-4.90)	(-5.27)	(-4.92)	(-4.00)	(-4.45)	(-3.85)	(-3.88)
B/M	0.069***	0.062***	1.701***	0.058***	0.053***	1.464***	1.050***	1.060***	1.251***	1.150***	1.163***	1.292***
	(5.62)	(4.81)	(16.56)	(4.79)	(4.13)	(14.09)	(16.06)	(14.52)	(12.74)	(17.11)	(15.47)	(12.88)
Ret_{t-1}	-0.002	-0.003	-0.010**	-0.019***	-0.019***	-0.029***	-0.028***	-0.030***	-0.022***	-0.030***	-0.032***	-0.024***
	(-0.99)	(-1.25)	(-2.52)	(-7.76)	(-7.06)	(-7.00)	(-11.48)	(-11.01)	(-5.40)	(-12.14)	(-11.68)	(-5.87)
Amihud	0.674***	1.652***	0.169	0.634***	1.584***	0.032	0.385**	1.078***	-1.125	0.355*	0.986***	-1.047
	(3.45)	(4.76)	(0.13)	(3.27)	(4.60)	(0.02)	(2.04)	(3.17)	(-0.89)	(1.88)	(2.90)	(-0.83)
Constant	0.062***	0.106***	0.053	0.167***	0.219***	0.110	0.066***	0.099***	-0.013	0.126***	0.165***	-0.003
	(6.67)	(6.52)	(0.86)	(10.15)	(10.06)	(1.62)	(7.27)	(6.22)	(-0.22)	(7.78)	(7.69)	(-0.05)
Observations	153,242	122,034	56,135	153,242	122,034	56,135	149,106	118,628	54,870	149,106	118,628	54,870
R-squared	0.017	0.018	0.029	0.034	0.035	0.047	0.021	0.022	0.031	0.022	0.023	0.031
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE				YES	YES	YES				YES	YES	YES

Table 5 Regression of idiosyncratic volatility and idiosyncratic emotion on excess return

This table provides regression results with control variables in the following model.

$$DGTW_{i,t} = a + b_1 EMO^{NS}_{i,t-1} + b_2 EMO^{S}_{i,t-1} + b_3 EMO^{N}_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Fama-Macbeth			Firm-Year Clustered Standard Errors			Three Lagged Newey-West Tests		
EMO^{NS}_{t-1}	0.005**			0.007***			0.007***		
	(2.05)			(2.67)			(3.19)		
EMO^{S}_{t-1}		0.003			0.004			0.004*	
		(1.12)			(1.27)			(1.72)	
EMO^{N}_{t-1}			-0.000			0.001			0.001
			(-0.00)			(0.45)			(0.26)
$IVOL_{t-1}$	0.019*	0.019*	-0.027	0.029**	0.026**	-0.011	0.029***	0.026***	-0.011
	(1.86)	(1.78)	(-1.53)	(2.38)	(2.20)	(-0.93)	(3.46)	(3.93)	(-0.97)
Beta	0.071	0.029	0.334	-0.021	-0.071	0.228*	-0.021	-0.071	0.228***
	(0.50)	(0.20)	(1.61)	(-0.21)	(-0.77)	(1.77)	(-0.44)	(-1.42)	(2.74)
Size	-0.001	-0.001	-0.001	0.001	0.000	-0.000	0.001	0.000	-0.000
	(-0.99)	(-1.20)	(-1.05)	(0.65)	(0.05)	(-0.23)	(1.00)	(0.08)	(-0.22)
B/M	-0.023	0.010	0.450	0.330	0.371*	0.243	0.330***	0.371***	0.243
	(-0.16)	(0.07)	(1.48)	(1.52)	(1.73)	(0.86)	(3.26)	(3.33)	(1.17)
Ret_{t-1}	-0.012*	-0.011	-0.001	-0.015	-0.016	-0.001	-0.015***	-0.016***	-0.001
	(-1.66)	(-1.43)	(-0.10)	(-1.31)	(-1.39)	(-0.13)	(-3.72)	(-3.86)	(-0.18)
Amihud	9.548	8.620	-611.545	0.209	0.532	-2.259	0.209	0.532	-2.259**
	(1.63)	(1.38)	(-1.45)	(0.83)	(1.05)	(-1.52)	(0.90)	(1.05)	(-2.38)
Constant	0.462*	0.419	-28.286	0.037**	0.054**	-0.101	0.037***	0.054**	-0.101**
	(1.70)	(1.45)	(-1.44)	(2.20)	(1.98)	(-1.35)	(3.31)	(2.27)	(-2.28)
Observations	149,106	118,628	54,870	149,106	118,628	54,870	149,106	118,628	54,870

Table 6 The effect of idiosyncratic volatility and idiosyncratic emotion on the risk component of DGTW excess return

This table provides the panel regression results with control variables and fixed effects in the following model.

$$RISK_{i,t} = a + b_1 EMO^{NS}_{i,t-1} + b_2 EMO^{S}_{i,t-1} + b_3 EMO^{N}_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where RISK is the risk components of return that are generated by regressing the DGTW excess returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing components. EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. Idiosyncratic volatility (IVOL) is the standard deviation of residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) factors following Ang et al. (2006). Other control variables include Beta, Size, B/M, and Amihud. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		RISK_DHS			RISK_SY			RISK_AFP	
EMO^{NS}_{t-1}	0.009***			0.010***			0.009***		
	(3.57)			(3.74)			(3.49)		
EMO^{S}_{t-1}		0.008**			0.008***			0.008**	
		(2.57)			(2.66)			(2.58)	
EMO^{N}_{t-1}			-0.001			-0.000			-0.002
			(-0.20)			(-0.02)			(-0.51)
$IVOL_{t-1}$	0.052***	0.051***	0.012*	0.047***	0.046***	0.008	0.051***	0.050***	0.013**
	(13.48)	(11.59)	(1.78)	(11.83)	(10.19)	(1.24)	(13.45)	(11.52)	(1.99)
Constant	0.072***	0.108***	-0.024	0.075***	0.118***	-0.024	0.072***	0.112***	-0.016
	(7.65)	(6.26)	(-0.40)	(7.76)	(6.66)	(-0.38)	(7.81)	(6.61)	(-0.27)
Observations	140,626	112,645	50,527	140,626	112,645	50,527	140,626	112,645	50,527
R-squared	0.022	0.023	0.031	0.035	0.038	0.031	0.020	0.021	0.032
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 7 The effect of idiosyncratic volatility and idiosyncratic emotion on the mispricing component of DGTW excess return
This table provides the panel regression results with control variables and fixed effects in the following model.

$$MP_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where MP is the mispricing components of return that are generated by regressing the DGTW excess returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing components. EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. Idiosyncratic volatility (IVOL) is the standard deviation of residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) factors following Ang et al. (2006). Other control variables include Beta, Size, B/M, and Amihud. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		MP_DHS			MP_SY			MP_AFP	
EMO_{t-1}^{NS}	0.000			-0.001			0.000		
	(0.49)			(-0.74)			(0.82)		
EMO_{t-1}^{S}		-0.000			-0.001			-0.000	
		(-0.40)			(-0.80)			(-0.85)	
EMO_{t-1}^{N}			-0.001			-0.001			0.001
			(-0.64)			(-1.41)			(0.92)
$IVOL_{t-1}$	-0.010***	-0.010***	-0.002	-0.003**	-0.003*	0.001	-0.007***	-0.007***	-0.003**
	(-9.90)	(-9.22)	(-1.46)	(-2.00)	(-1.92)	(0.36)	(-9.09)	(-9.03)	(-2.54)
Constant	-0.004*	0.000	0.003	-0.007*	-0.012	0.004	-0.002	-0.002	-0.006
	(-1.73)	(0.05)	(0.21)	(-1.81)	(-1.62)	(0.29)	(-1.37)	(-0.54)	(-0.56)
Observations	144,452	115,798	51,682	144,452	115,798	51,682	144,452	115,798	51,682
R-squared	0.035	0.037	0.030	0.133	0.126	0.043	0.038	0.040	0.051
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 8 The effect of idiosyncratic volatility and idiosyncratic emotion on return with different institutional ownership measures

This table provides the panel regression results with control variables and fixed effects in the following model.

$$DGTW_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{NS} * IO_{i,t-1} + b_3 IO_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. IO are institutional ownership measures using Thomson-Reuters 13F data. IO Ratio is the IO Level divided by total shares outstanding at quarter end. Institutional Concentration (IC) is captured by the Herfindahl-Hirschman Index that uses all institutional holdings of a particular security and conveys information about institutional ownership distribution. Institutional Breadth (IB) simply represents the number of institutions owning the stock during the quarter. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		IO Ratio			IC			IB	
EMO_{t-1}^{NS}	0.014***			0.015***			0.011***		
	(4.73)			(4.54)			(4.32)		
EMO_{t-1}^{S}		0.015***			0.014***			0.011***	
		(4.08)			(3.70)			(3.67)	
EMO_{t-1}^{N}			0.008*			0.004			0.001
			(1.71)			(0.74)			(0.19)
$EMO_{t-1}^{NS} * IO_{t-1}$	-0.038**			0.010**			-0.001		
	(-2.08)			(2.02)			(-0.57)		
$EMO_{t-1}^{S} * IO_{t-1}$		-0.052**			0.010*			-0.005*	
		(-2.41)			(1.80)			(-1.73)	
$EMO_{t-1}^{N} * IO_{t-1}$			-0.066**			0.007			-0.003
			(-2.33)			(1.04)			(-0.79)
IO_{t-1}	0.135***	0.196***	0.102**	-0.028***	-0.036***	-0.024**	-0.018***	-0.015***	-0.013***
	(4.40)	(5.39)	(2.13)	(-4.58)	(-4.97)	(-2.26)	(-5.45)	(-3.75)	(-2.81)
Constant	0.128***	0.172***	0.005	0.120***	0.164***	-0.002	0.122***	0.163***	0.006
	(7.93)	(8.00)	(0.07)	(7.35)	(7.61)	(-0.02)	(7.54)	(7.57)	(0.09)
Observations	148,084	117,890	54,494	148,092	117,896	54,499	148,092	117,896	54,499
R-squared	0.022	0.024	0.032	0.022	0.024	0.032	0.022	0.023	0.032
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 9 The effect of idiosyncratic emotion on return with retail ownership

This table provides the 2SLS and OLS regression results using retail ownership. Following Iselin et al. (2022), we compute the retail ownership by adding total institutional ownership and total insider ownership and assuming the remaining ownership is composed of retail owners. In columns (1) and (2), we perform the two stage least square approach, Column (1) shows the first-stage regression result where the idiosyncratic emotion is regressed on the retail ownership. Column (2) shows the second stage. The dependent variable is DGTW excess return calculated following Daniel et al (1997). The columns (3) and (4) provides the panel regression results with control variables and fixed effects in the following model.

$$DGTW_{i,t} = a + b_1 EMO^{NS}_{i,t-1} + b_2 EMO^{NS}_{i,t-1} * Retail_{i,t-1} + b_3 Retail_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where EMO_{NS} is the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from news and social media content. Retail is the decile sorted by retail ownership measured using the Thomson-Reuters 13F database and the Execucomp database. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
	EMO^{NS}_{t-1}	$DGTW_{i,t}$	$DGTW_{i,t}$	$DGTW_{i,t}$
$Retail\%$	-0.017***			
	(-5.81)			
EMO^{NS}_{t-1}		0.461***	0.005**	-0.006
		(2.6)	(2.25)	(-1.33)
$Retail_{t-1}$			-0.010***	-0.010***
			(-11.08)	(-11.11)
$EMO^{NS}_{t-1} * Retail_{t-1}$				0.003***
				(2.88)
Constant	0.043***	0.006	0.081***	0.081***
	(4.39)	(0.39)	(8.62)	(8.67)
Observations	152,506	148,373	148,373	148,373
Control	YES	YES	YES	YES

Table 10 The effect of idiosyncratic volatility and idiosyncratic emotion on return with different firm characteristics

This table provides the panel regression results with control variables and fixed effects in the following model.

$$DGTW_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{NS} * FIRM_{i,t-1} + b_3 FIRM_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. FIRM are firm characteristics related to advertising expenditure (ADV/SALE), research and development (R&D/SALE), and labor expenses (STAFF/SALE). All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)
		ADV/SALE	
EMO_{t-1}^{NS}	0.009***		
	(3.71)		
EMO_{t-1}^{S}		0.010***	
		(3.27)	
EMO_{t-1}^{N}			-0.003
			(-0.75)
$EMO_{t-1}^{NS} * FIRM_{t-1}$	0.017**		
	(2.42)		
$EMO_{t-1}^{S} * FIRM_{t-1}$		0.001	
		(0.11)	
$EMO_{t-1}^{N} * FIRM_{t-1}$			0.099**
			(2.52)
$FIRM_{t-1}$	-0.015***	-0.015***	0.036
	(-2.93)	(-2.80)	(1.32)
Constant	0.128***	0.167***	-0.007
	(7.97)	(7.87)	(-0.11)
Observations	147,548	117,188	54,617
R-squared	0.022	0.024	0.032
Control	YES	YES	YES
Firm-Year FE	YES	YES	YES

Table 11 The effect of idiosyncratic volatility and idiosyncratic emotion on return with fixed effects for different periods.
This table provides the panel regression results with control variables and fixed effects in the following model.

$$DGTW_{i,t} = a + b_1 EMO^{NS}_{i,t-1} + b_2 EMO^{S}_{i,t-1} + b_3 EMO^{N}_{i,t-1} + b_4 Control_{i,t-1} + \epsilon_{i,t}$$

where DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(2)	(3)	(4)	(6)	(7)	(8)
	1999-2007			2008-2017		
EMO^{NS}_{t-1}	0.008*			0.012***		
	(1.94)			(3.62)		
EMO^{S}_{t-1}		0.003			0.012***	
		(0.72)			(3.08)	
EMO^{N}_{t-1}			-0.011*			0.002
			(-1.69)			(0.56)
$IVOL_{t-1}$	0.056***	0.057***	0.014	0.029***	0.022***	0.011
	(6.91)	(6.82)	(0.82)	(6.14)	(4.03)	(1.44)
Beta	-0.559***	-0.604***	-0.015	0.118	0.131	0.326***
	(-4.99)	(-5.16)	(-0.06)	(1.59)	(1.53)	(2.70)
Size	-0.030***	-0.030***	-0.014***	-0.013***	-0.010***	-0.012***
	(-5.18)	(-4.98)	(-3.24)	(-3.59)	(-2.74)	(-3.84)
B/M	2.220***	2.251***	3.473***	1.180***	1.273***	1.298***
	(13.07)	(12.73)	(8.54)	(15.12)	(13.88)	(11.84)
Ret_{t-1}	-0.048***	-0.049***	-0.034***	-0.025***	-0.028***	-0.027***
	(-11.75)	(-11.37)	(-3.40)	(-8.34)	(-8.01)	(-6.07)
Amihud	0.948**	0.938**	33.118	0.043	0.258	-0.881
	(2.50)	(2.42)	(0.37)	(0.20)	(0.33)	(-0.67)
Constant	0.201***	0.212***	1.678	0.046***	0.049	0.012
	(8.91)	(9.02)	(0.41)	(3.20)	(1.30)	(0.19)
Observations	54,591	50,479	9,084	94,515	68,149	45,786
R-squared	0.027	0.028	0.066	0.029	0.032	0.034
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 12 The effect of idiosyncratic volatility and idiosyncratic emotion on return with fixed effects for recessionary and expansionary periods
This table provides the panel regression results with control variables and fixed effects in the following model.

$$DGTW_{i,t} = a + b_1EMO_{i,t-1}^{NS} + b_2EMO_{i,t-1}^{S} + b_3EMO_{i,t-1}^{N} + b_4Control_{i,t-1} + \epsilon_{i,t}$$

where DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
		recession			expansion	
EMO_{t-1}^{NS}	0.004			0.011***		
	(0.31)			(4.29)		
EMO_{t-1}^{S}		0.013			0.009***	
		(0.96)			(3.00)	
EMO_{t-1}^{N}			-0.013			-0.001
			(-0.63)			(-0.26)
$IVOL_{t-1}$	0.067***	0.077***	0.056**	0.035***	0.027***	0.015**
	(5.72)	(6.10)	(2.18)	(7.90)	(5.36)	(2.10)
Beta	1.959***	1.903***	1.349**	-0.207***	-0.246***	0.242**
	(6.98)	(6.19)	(2.18)	(-3.81)	(-3.99)	(2.47)
Size	0.006	0.009	0.009	-0.011***	-0.011***	-0.008***
	(0.44)	(0.59)	(0.68)	(-4.82)	(-4.25)	(-4.18)
B/M	2.180***	2.022***	1.513***	1.097***	1.118***	1.282***
	(9.48)	(8.23)	(4.59)	(14.98)	(13.57)	(11.35)
Ret_{t-1}	-0.054***	-0.061***	0.001	-0.032***	-0.033***	-0.035***
	(-8.08)	(-8.50)	(0.04)	(-11.90)	(-10.99)	(-8.29)
Amihud	0.836	0.813	18.917	0.277	1.453***	-1.271
	(1.37)	(1.30)	(0.61)	(1.38)	(2.98)	(-1.05)
Constant	0.021	0.027	0.871	0.126***	0.190***	-0.016
	(0.64)	(0.76)	(0.61)	(7.81)	(7.21)	(-0.26)
Observations	16,416	13,979	4,741	132,690	104,649	50,129
R-squared	0.072	0.078	0.065	0.025	0.026	0.036
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table13 Cross Validation of the effect of idiosyncratic volatility and idiosyncratic emotion on return with six behavioral risk proxies
This table provides the panel regression results containing six behavioral risk proxies in the following model.

$$R_{i,t} = a + b_1 EMO_{i,t-1}^{NS} + b_2 EMO_{i,t-1}^{S} + b_3 EMO_{i,t-1}^{N} + b_4 Control_{i,t-1} + b_5 \text{Indices}_{i,t-1} + \epsilon_{i,t}$$

where Ret is the raw CRSP monthly return, DGTW is the excess return calculated following Daniel et al (1997), EMO_N, EMO_S and EMO_{NS} are the standard deviation of residuals from a regression of the first principal component of firm-specific emotions on the market-level emotions from different content sources: news, social media, and the combined content. We include six novel behavioral risk proxies for emotion arousal: two investor sentiment indices from Baker et al. (2006) (SENT, SENT_ORTH), Consumer Confidence Index from University of Michigan (CCI), Market-wide volatility measure (VIX), three-components economic policy uncertainty index (EPU_1), and News-based EPU index (EPU_2). Panel A reports the pairwise correlation of idiosyncratic emotion with six proxies. All control variables are consistent with previous Tables. The t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Pairwise correlation among EMO and six proxies	SENT	SENT_ORTH	VIX	CCI	EPU_1	EPU_2
EMO^{NS}	-0.1331**	-0.1195*	-0.1217*	0.0711	-0.1905***	-0.2468***
Panel B: Cross validation regression	(1)	(2)	(3)	(4)	(5)	(6)
		RET			DGTW	
EMO_{t-1}^{NS}	0.009***			0.010***		
	(3.61)			(4.21)		
EMO_{t-1}^{S}		0.006**			0.009***	
		(2.02)			(2.95)	
EMO_{t-1}^{N}			0.001			-0.001
			(0.23)			(-0.20)
SENT	0.509***	0.539***	0.270***	0.097***	0.110***	0.052**
	(28.49)	(26.03)	(10.46)	(5.51)	(5.38)	(2.04)
SENT_ORTH	-0.544***	-0.576***	-0.337***	-0.080***	-0.094***	-0.041*
	(-31.28)	(-28.54)	(-13.69)	(-4.63)	(-4.69)	(-1.71)
VIX	-0.025***	-0.025***	-0.025***	-0.002***	-0.002***	-0.002***
	(-67.33)	(-58.43)	(-49.61)	(-5.47)	(-4.45)	(-4.97)
CCI	-0.001***	-0.001***	-0.004***	0.001***	0.001***	-0.000
	(-5.38)	(-3.70)	(-10.74)	(3.37)	(3.36)	(-0.64)
EPU_1	0.003***	0.004***	0.002***	0.000**	0.000**	0.000
	(20.26)	(17.52)	(10.24)	(2.04)	(2.25)	(0.34)
EPU_2	-0.002***	-0.002***	-0.002***	-0.000***	-0.001***	-0.000
	(-19.32)	(-16.57)	(-10.57)	(-3.56)	(-4.12)	(-1.10)
Constant	0.050	0.073*	0.079	0.050	0.073*	0.079
	(1.55)	(1.87)	(1.10)	(1.55)	(1.87)	(1.10)
Observations	149,106	118,628	54,870	149,106	118,628	54,870
R-squared	0.022	0.023	0.031	0.022	0.023	0.031