GIFfluence:

A Visual Approach to Investor Sentiment and the Stock Market

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We study dynamic visual representations as a proxy for investor sentiment and their relation to stock market outcomes. Our sentiment index, GIFsentiment, is constructed from millions of posts containing visuals in the Graphics Interchange Format (GIF) on a leading investment social media platform. GIFsentiment correlates with seasonal mood variations and the severity of COVID lockdowns. It is positively associated with contemporaneous market returns and negatively with returns in the subsequent four weeks, even after controlling for other sentiment measures. These effects are stronger among portfolios of stocks that are more susceptible to mispricing. GIFsentiment positively predicts trading volume, market volatility, and flows toward equity funds and away from debt funds. Our evidence suggests that GIFsentiment is a proxy for misperceptions that are later corrected. These findings highlight the growing influence of visual media in investor communication and suggest that emotionally expressive GIFs reflect behavioral biases that shape investor decision-making and market outcomes.

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1 Introduction

Social media users often use pictures or short videos to convey ideas and emotions to others. When dynamic visual representations are provided by investors, they can reflect the thoughts and feelings underlying their trading decisions in the financial markets. This study examines the relation between dynamic visuals in investors' social media communications and stock market outcomes.

Specifically, we focus on the Graphics Interchange Format (GIF), a popular visual format that uses short looping video animations to vividly convey emotions and ideas, often with a humorous twist.[1] GIFs are widely shared and highly effective at expressing sentiment (Milner and Highfield 2017), suggesting that they may serve as proxies for investor sentiment.

To test this, we construct a novel investor sentiment index, GIFsentiment, by analyzing GIFs shared in social media communications about the stock market. We then evaluate whether GIFsentiment predicts market returns, trading volume, volatility, and equity versus bond fund flows. To our knowledge, this is the first study to directly relate GIF visuals to market sentiment and stock market outcomes.

GIFs are powerful communication tools that are often more effective than text, in capturing attention and conveying ideas and feelings. Their integration of motion and sequential images uniquely encapsulates ideas about past events, future forecasts, or cause-and-effect relationships in the form of mini-stories, making them highly engaging.[2] The salience of GIFs makes them especially effective in capturing the attention of receivers.

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[1] See https://gmis.me/Animated_GIF_Examples_and_their_Static_Counterparts.htm for some examples comparing GIFs and still images. An anecdotal example of the association of GIF use with market outcomes is the 6.3% drop in the stock price of Tesla on the day a GIF of Elon Musk apparently smoking marijuana in a Joe Rogan podcast went viral; see the GIF at https://giphy.com/gifs/3jcgPn9fzfaXc1EHJC.

[2] Images and motion are triggers for bottom-up attention, which is an effortless and automatic response to a salient stimulus (see, e.g., Li and Camerer 2022). GIFs can also engage with top-down attention, which is effortful and deliberative, as GIFs can highlight a key idea or topic of interest to the recipient.

Neuroscience research on social cognition shows that visuals have a profound effect on thinking. A large part of the human cerebral cortex is dedicated to processing visual stimuli. The tendency to focus on visual stimuli is supported by the findings of Fiske and Taylor (2020) and Dragoi and Tsuchitani (2016). In a similar vein, tech leaders have also emphasized that combining visuals with text (multimodality) is key for effective communication and message delivery.[3]

Furthermore, GIFs portray motion, which is a powerful attentional cue. Motion triggers physiological arousal, thereby increasing the likelihood of action or response. Compared to static images, visual motion elicits stronger physiological arousal as measured by skin conductance (Detenber et al. 1998; Fox et al. 2004; Simons et al. 1999). This heightened arousal is linked to more extreme evaluations, enhanced long-term memory (Storbeck and Clore 2008), increased risk-taking (FeldmanHall et al. 2016), autonomic responses and impulsive decision-making (Herman, Critchley, and Duka 2018), suggesting that GIFs may induce impulsive investor decisions.

GIFs are vivid (on vividness, see Nisbett and Ross 1980) in the sense of being emotionally engaging, concrete, and imagery-rich sources of information. This makes GIFs more effective in attracting attention, improving recall, and influencing attitudes. The succinctness (Potter et al. 2014) of GIFs and their unique immediacy (Bakhshi et al. 2016) also enhance emotional intensity, making them instantly understandable and highly engaging in expressing emotions and telling stories. For attention-constrained investors, these features make GIFs an efficient medium for communicating. We therefore expect GIFs to capture investor sentiment.

Finally, GIFs also have the ability to depict sequences of events, making them particularly suited to conveying understandings of past or future events. This allows GIFs to represent simple mental models or narratives about the stock market (Shiller 2017; Hirshleifer 2020; and Andre, Schirmer, and Wohlfart 2024). For example, a GIF of a rocket launching toward the moon can represent an anticipated rapid rise in stock price, thereby inducing or reflecting investor sentiment.

[3] See, for example, the discussion between OpenAI co-founder Ilya Sutskever and Nvidia Founder and CEO Jensen Huang in Highlights of the Fireside Chat AI Today & Vision of the Future starting at 00:23:47.

Based on these considerations, we use GIFs to construct a novel proxy for investor sentiment. Specifically, we introduce a daily aggregate market-level investor sentiment index, GIFsentiment, derived from GIFs embedded in messages posted on Stocktwits.com, a leading online platform for sharing opinions about stocks and financial assets. We then examine the relation between GIFsentiment and market outcomes, comparing it to other established sentiment proxies from previous literature to assess its incremental predictive power.

We first examine whether GIFsentiment is associated with sentiment proxies from the previous literature. Behavioral theories predict that an investor sentiment proxy will be positively associated with contemporaneous returns as overvaluation grows and will negatively predict returns in subsequent periods when overvaluation is corrected. To evaluate whether GIF sentiment is an investor sentiment proxy, we therefore test whether GIF sentiment has a positive contemporaneous association with equity index returns and whether it negatively forecasts subsequent returns. We further test whether these sentiment index properties hold incrementally after controlling for five other sentiment proxies from past literature. We also examine whether its association with returns on aggregate indices that differ in size or idiosyncratic volatility and test its relation to trading volume, short-selling activity, market volatility, and equity and bond fund flows.

To classify GIF sentiment on a large scale, we exploit a feature on Stocktwits that allows users to self-declare their posts as bullish or bearish. We define a unique GIF as a specific animated image (e.g., a rocket shooting toward the moon), treated as a single unit regardless of how many times it appears across posts. For each unique GIF, we tally its appearances in bullish- and bearish-labeled posts and compute its net bullish sentiment. Crucially, this GIF-level net bullish sentiment allows us to gauge the net optimism of all posts that contain GIFs—even posts that do not have sentiment declarations. We then derive the aggregate market sentiment for that day, GIFsentiment, by combining the net optimism measures for all GIF-containing posts for any given date.

Specifically, we quantify each unique GIF's valence as the proportion of net bullish declarations (bullish minus bearish declarations), divided by the total appearances. To avoid look-ahead bias, we calculate this continuous GIF-level sentiment measure using a forward expanding window, updated daily. The aggregate daily GIFsentiment is the appearance-weighted average valence of these unique daily GIF sentiment scores; details in Subsection 2.2.

Our sample spans September 2020—when Stocktwits introduced an in-composer GIPHY search button—through October 2024. GIPHY, one of the largest GIF repositories worldwide, allows users to search and insert GIFs easily, enabling more vivid expression of sentiment. Stocktwits also includes a dedicated bullish or bearish button throughout our sample period, allowing users to give a binary declaration of their sentiment as a part of their posts.

Users who self-identify as novice investors on Stocktwits are more likely to use GIFs to express sentiment, while intermediate and professional investors favor explicit bullish or bearish declarations. This may be due to the psychological nature, visual salience, emotional expressiveness, and narrative framing of GIFs, which could appeal more to investors prone to behavioral biases.

Our main tests assess the predictive power of GIFsentiment for market outcomes and its incremental contribution beyond the five sentiment measures detailed in Section 2.3, namely TEXTsentiment, monthly Baker and Wurgler (2006) sentiment measure BW, monthly University of Michigan consumer sentiment index ICS, MEDIAsentiment from RavenPack, and SELFDEC derived from self-declared bullish or bearish sentiment in postings without GIFs to isolate the unique effects of GIFsentiment. These sentiment measures are pairwise significantly correlated, suggesting a commonality in what they capture.[4]

The first set of tests seeks to evaluate the sentiment measures by assessing their

[4] Obaid and Pukthuanthong (2022) develop a proxy for investor sentiment based upon human ratings of still photos. As it is not straightforward to acquire large numbers of news media photos and generate human ratings of them, we do not use their sentiment measure as a control in our tests. However, we discuss their findings and some advantages of using GIF sentiment relative to hiring people to rate still images in Section 2.

associations with several time-varying mood proxies for investor feelings identified in past research. The mood proxies include an optimism indicator, *PositiveMonths* (Thaler 1987; Hirshleifer, Jiang, and DiGiovanni 2020), and several pessimism indicators: *NegativeMonths* (Kamstra et al. 2017), deseasonalized cloud cover DCC (Hirshleifer and Shumway 2003), and the change in the COVID stringency index, ΔCOVID, reflecting increased government lockdown restrictions (Terry, Parsons-Smith, and Terry 2020; Bueno-Notivol et al. 2021).

Consistent with GIFsentiment capturing investor mood, we find that GIFsentiment is lower on days with higher cloudiness and when government lockdown restrictions became stricter, and during months with declining mood. In contrast, the other sentiment measures do not exhibit consistent associations across mood proxies, suggesting that these measures may not primarily reflect variation in mood.

We also examine the association of all six sentiment indexes with a measure of aggregate earnings news to test if they capture reactions to contemporaneous fundamental news separately from sentiment. We define a firm's earnings announcement outcome as non-negative if earnings meet or beat consensus analyst forecasts and define aggregate earnings news as the fraction of earnings announcement outcomes that are non-negative on the given day. We find that GIFsentiment and BW are not significantly correlated with aggregate earnings news, while the four other proxies are. These results suggest that GIFsentiment offers a more direct reflection of investor mood and attention, whereas the other sentiment measures concurrently also capture rational reactions to fundamental news.

Our main tests examine the predictability of sentiment for market outcomes consistent with the investor sentiment model of De Long et al. (1990). According to this model, high investor sentiment produces market overpricing followed by low subsequent returns. This occurs because sentiment-driven investors increase their demand for risky assets in high sentiment periods, driving prices above fundamentals. An opposite dynamic occurs when sentiment is low.

We find that GIFsentiment is positively correlated with contemporaneous aggregate stock market returns and is a negative predictor of market returns during the first month after the sentiment conditioning date. This negative return predictability suggests that our GIFsentiment measure is capturing mispricing rather than fundamental information. In terms of magnitudes, a one standard deviation increase in GIFsentiment is associated with an additional 20 basis points on the contemporaneous S&P 500 index return, and a return that is lower by 23.5 basis points in the first week and 106.8 basis points in the first month.[5] These effects are present, controlling for contemporaneous fundamental events using daily news-based measures of U.S. economic policy uncertainty, EPU (Baker et al. 2016) and daily U.S. macroeconomic activity index, ADS (Aruoba et al. 2009). We also control for two proxies of investor attention: (1) attention to fundamental financial news, measured by the log of the number of earnings announcements on a given day (Log#EA; Hirshleifer, Lim, and Teoh 2009), and (2) general social media attention, proxied by the deviation from the median number of messages posted over the prior 10 trading days (Cookson, Lu, Mullins, and Niessner 2024). Overall, there is no indication that economic fundamentals or the prior investor attention proxy drive these effects, and the magnitudes of the GIFsentiment coefficients are economically meaningful.

To determine if these findings derive from the unique characteristics of GIFs—that they are dynamic visual representations—we estimate the incremental effect of GIFsentiment when including the other five sentiment measures. Even with these other measures included, GIFsentiment remains highly significant, showing a strong positive association with contemporaneous market returns and a strong negative association with one-month forward returns. These findings also hold in the intraday specifications, where GIFsentiment shows a strong negative association with two-day forward returns.

In sharp contrast, the findings for the other sentiment measures are not systematically

[5] The fact that the post-conditioning date returns exceed the conditioning date returns suggests that high daily GIF sentiment may partly reflect sentiment and overpricing present prior to the conditioning date.

consistent with the predictions of the investor sentiment model. For example, TEXTsentiment is positively associated with contemporaneous returns but also with subsequent one-month returns, and BW exhibits the opposite pattern of a negative relation with contemporaneous, one-week and one-month returns.

Thus far, only GIFsentiment exhibits robust evidence consistent with the predictions of the investor sentiment model. The De Long et al. (1990) investor sentiment model further suggests that greater investor bias creates greater initial mispricing, and that limits to arbitrage constrain the speed of correction toward fundamentals induced by rational investors (Pontiff 1996; Shleifer and Vishny 1997). Therefore, we expect the overreaction and correction dynamic to be strongest among assets most sensitive to investor psychological bias, and those that are riskier and costlier to arbitrage. Small stocks are likely more sensitive to retail investor sentiment and less liquid, which limits arbitrage (Lee, Shleifer and Thaler 1991). High uncertainty stocks (as proxied, e.g., by idiosyncratic volatility) are also likely more sensitive to investor sentiment shocks and riskier to arbitrage (Pontiff 1996; Baker and Wurgler 2006).

To test these further predictions of the investor sentiment hypothesis, we examine major US equity indices and portfolios constructed based on firm size, idiosyncratic volatility, and total return volatility. Consistent with the predictions, GIFsentiment exhibits stronger return predictability in portfolios that are most susceptible to psychological bias and pose the greatest cost to arbitrage. These include the smallest firm size quintile and the highest quintiles of idiosyncratic and total return volatility.

In our next set of tests, we examine the prediction of past theoretical and empirical literature that investor sentiment-driven noise trading increases stock return volatility (Black 1986; Da, Engelberg, and Gao 2015). We hypothesize a positive relationship between absolute sentiment and stock market volatility. As an alternative hypothesis, if a sentiment measure contains substantial information about fundamentals, extreme values of the measure could reflect the arrival of

information that resolves uncertainty on the conditioning date, reducing forward-looking volatility.

We find a positive relation between absolute GIFsentiment and return volatility for the week after the conditioning date. In contrast, we find a negative relation between absolute sentiment and next week's stock market volatility for all the other sentiment measures except MEDIAsentiment. These findings imply that GIFsentiment captures investor sentiment largely unrelated to fundamentals, while other sentiment measures, except for MEDIAsentiment, seem to reflect some fundamental information that resolves uncertainty.

We also explore the relation between GIFsentiment and trading activity. We hypothesize that more extreme sentiment promotes greater disagreement and trading activity, as sentiment-prone investors trade more heavily against sentiment-resistant investors. Since mean GIFsentiment is normalized to zero, extremity is captured by the absolute value of GIFsentiment. Consistent with our hypothesis, absolute GIFsentiment is positively associated with trading volume.

Finally, we study the link between GIFsentiment and retail investors behavior. Retail investors—often characterized as noise traders in prior literature—hold a large share of U.S. mutual fund assets.[6] Our tests examine whether GIFsentiment predicts equity and bond fund flows, using daily mutual fund flows as a proxy for aggregate noise trading at the asset-class level. To capture shifts in optimism, we focus on flows into U.S. equity versus bond funds.

We find that increases in GIFsentiment predict substantial same-day and subsequent-week inflows into equity funds and outflows from bond funds. Coupled with our evidence that high GIFsentiment is associated with greater subsequent volatility, this pattern represents a "flight from safety", in sharp contrast to the "flight to safety" documented in prior research (Baele et al. 2020). Investors may not prefer risk per se but are drawn to it when sentiment is high.

Our findings indicate GIFsentiment captures attention and feelings more sharply than alternative sentiment measures do. Unlike these alternatives, GIFsentiment strongly correlates

[6] The Investment Company Institute's research reveal that 116 million individual investors hold mutual funds in 2023, a significant increase from 86 million in 2005.

with established mood proxies but not with fundamental news, and consistently predicts negative returns over the subsequent month.

To sum up, we provide a new measure of aggregate market sentiment based on dynamic visual representations that predicts aggregate trading, fund flows, and stock market returns incremental to existing sentiment measures. Several authors have argued that shifts in investor sentiment are driven by social interaction (Shiller 2017; Hirshleifer 2020; Kuchler and Stroebel 2021; Cookson, Mullins, and Niessner 2024). Unlike most existing sentiment measures that have been applied to the aggregate stock market, GIFsentiment is based on posts on social media. As such, our paper contributes to the growing field of social finance. We also document that GIFsentiment is, in several respects, a sharper sentiment proxy than those used in prior literature.

Our paper builds on existing literature that uses proxies for investor sentiment to predict stock returns in either the cross-section or in the aggregate. In addition to the papers on sentiment and the cross-section of returns discussed earlier, Gu et al. (2023) use a GIFsentiment measure to predict returns across individual stocks. Our paper differs in testing the implications of aggregate GIFsentiment for aggregate trading and returns.

Past aggregate stock market predictors include dividend yield and investor sentiment proxies such as cloud cover, sports results, or media discourse.[7] Our paper differs in developing a dynamic visual-based sentiment measure from social media postings, GIFsentiment, which captures variations in mood and attention. This approach highlights the social transmission of investor sentiment, thereby reflecting how feelings spread from person to person rather than taking the sole form of isolated reactions to mass media.[8]

[7] Some papers use individual sentiment proxies to predict returns at horizons of up to one week (Hirshleifer and Shumway 2003, Edmans, Garcia, and Norli 2007, Da, Engelberg, and Gao 2015, and Obaid and Pukthuanthong 2022). Other individual proxies have been found to predict returns at horizons of many months, such as fund flows (Ben-Rephael, Kandel and Wohl 2012) and war discourse in the news media (Mai, Hirshleifer, and Pukthuanthong 2024). Huang et al. (2015) find that a combination of multiple sentiment proxies predicts one-month-ahead returns.
[8] Our paper also differs from some of these measures that are based in part on market prices. Market price based proxies are expected to predict returns as prices reflect both risk premia and expectations. As such, it is harder to clearly distinguish sentiment effects from risk premium effects using price-based measures.

2 Sentiment Measures and Mood Proxies

This section details our sentiment measures and mood proxies, beginning with a comparison of GIFsentiment to existing literature (Subsection 2.1) and the construction of GIFsentiment (Subsection 2.2). We then describe alternative sentiment measures used as controls (Subsection 2.3) and evaluate GIFsentiment's validity through its association with established mood proxies (Subsection 2.4).

2.1 Literature on investor sentiment proxies

Previous research quantifies investor sentiment using surveys, combinations of economic variables, and textual analysis from various sources to forecast stock market returns and other outcomes. Other studies also employ event shocks, such as morning sunshine (Hirshleifer and Shumway 2003) and sports outcomes (Edmans, Garcia, and Norli 2007) as proxies for investor mood.

Survey-based measures include the Michigan Consumer Index (Qiu and Welch 2004) and the American Association of Individual Investors (AAII) monthly sentiment survey of the views of individual investors about the next six months. The classic Baker and Wurgler (2006) sentiment index, BW, is constructed from the first principal component of six economic variables– NYSE turnover, the dividend premium, IPO activity and their first-day returns, the closed-end fund discount, and the equity share in new issues. Sentiment has also been gauged from fund flows, as in the study of Ben-Rephael, Kandel and Wohl (2012).

Textual sentiment measures are constructed from media articles, financial reports, and social media postings, typically using word frequencies or expressed opinions (e.g., Tetlock 2007; Loughran and McDonald 2011; Da, Engelberg, and Gao 2015; Chen et al. 2014; Cookson and Niessner 2020). Sentiment has also been extracted from non-textual media, such as music billboard charts (Edmans et al. 2022).

A challenge in deriving sentiment measures from social media text or visuals is ecological validity: ensuring that social media context aligns with the investing context. General platforms like Twitter include a broad set of participants, many with limited or no interest or participation in the stock market. Similarly, Amazon Mechanical Turk (MTurk) raters are unlikely to be active investors, so the use of such raters to train machine-learning sentiment models creates a mismatch with the target investor population. Despite this challenge, Obaid and Pukthuanthong (2022) developed a visual sentiment proxy using 148,823 static news photos from the Wall Street Journal (WSJ) that predicted aggregate returns one week ahead.[9] Their daily pessimism index was trained using 882 Twitter photos. This suggests an approach of dynamic visuals with improved context matching may capture sentiment more powerfully.

Our method mitigates context mismatch by utilizing Stocktwits' native environment, extracting GIF sentiment directly from users' self-declarations. These individual posters are typically active or interested stock market participants, ensuring ecological validity. The use of self-declarations also provides a natural 'ground truth' about investor attitudes that is unavailable for most other sentiment proxies in the literature. This approach also avoids concerns about the use of external raters such as undergraduates or MTurkers—high costs, small training sample size, limited incentives, and possible mismatch of the sample with equity investors owing to limited exposure to the stock market (Saravanos et al. 2021; Aguinis, Villamore, and Ramani 2021).

We test for GIFsentiment's incremental association with stock market outcomes along with other sentiment measures from the literature, including text-based sentiment, Baker-Wurgler sentiment, the Michigan Consumer Index, and traditional media sentiment. Their construction is described in Subsection 2.3. While other studies examine static visuals in corporate communications and their firm-level association with investor perceptions (Blankespoor, Hendricks, and Miller 2017; Nekrasov, Teoh, and Wu 2022; Peng et al. 2022; Christensen et al.

[9] The authors validated the pessimism label assigned by their machine learning algorithm against labels assigned by five MTurk raters for a sample of 100 WSJ photos.

2024; and Ronen et al. 2023),[10] our study tests for a predictive relation between sentiment derived from dynamic visual representations and aggregate stock market outcomes.

2.2 Construction of GIFsentiment

Launched in 2008, Stocktwits.com initially supported text and hyperlinks. In September 2020, users gained the ability to add GIFs via a menu button linking to Giphy.com, one of the largest global GIF search engines, enhancing their expressive capabilities.

Stocktwits posts offer several features that facilitate the construction of a high-frequency sentiment measure. Each post has a date and time stamp, enabling daily sentiment measurement. Users can specify stocks via cashtags (e.g., $AAPL for Apple Inc.) and multiple cashtags can be used for discussions of several stocks. This feature helps identify stock-related posts, indicating broader attention to the equity market.

GIFs in Stocktwits posts are identifiable by their .gif URLs, and unique Giphy.com identifiers,[11] allowing for accurate tracking of individual GIFs. Our sample, from September 1, 2020 to October 31, 2024, comprises 65 million posts cashtags,[12] of which 5.5 million contain visuals and 463,227 are unique. Stocktwits introduced a bullish or bearish declaration feature in September 2012. Building on other research that uses these declarations as a message sentiment proxy (e.g., Cookson and Niessner 2020, Cookson et al. 2023, Cookson et al. 2024), we exploit posts with both GIFs and self-declarations to infer sentiment for the same GIFs in posts lacking

[10] Blankespoor, Hendricks, and Miller (2017) analyze video clips of IPO roadshows to assess investor perceptions of CEOs. Nekrasov, Teoh, and Wu (2022) study firms' use of static images in earnings-related tweets. Christensen et al. (2024) explore the types and placement of infographics in 10-K filings, examining factors influencing their usage and persistence over time. Ronen et al. (2023) introduce a machine learning-based measure to quantify the informativeness of images on equity crowdfunding pitch webpages, and to link image characteristics to fund investment decisions.

[11] Stocktwits partners with Giphy.com, the world's largest GIF search engine, to enable users to the select and post GIFs seamlessly. All GIF URLs on Stocktwits.com are hosted on Giphy.com and share a uniform hyperlink structure: https://media2.giphy.com/media/{gif.id}/giphy.gif.

[12] Past studies of Stocktwits (e.g., Cookson and Niessner 2022, Cookson, Engelberg, and Mullins 2023, Gu, Teoh, and Wu 2023) exclude posts with multiple cashtags so that each posting can be linked to a particular stock to enable the construction of a firm-specific sentiment measures. In contrast, in this study, we use StockTwits posts to construct aggregate-level measures, so we do not need to remove post mentioning multiple tickers.

explicit declarations.

We construct a daily sentiment label for each unique GIF using the daily count of associated bullish and bearish declarations, ensuring no look-ahead bias. Over our sample, 96% of GIFs had at least one declaration, 71% had five or more, and 50% had 25 or more. To ensure consensus, we include only GIFs with at least five declarations.[13] This minimum threshold is comparable to the number of human raters used in other studies. This method essentially calibrates the positive or negative sentiment of each unique GIF by aggregating self-declared expressions of optimism and pessimism across multiple posts, enabling inference for GIF-containing posts without explicit declarations.

We calculate the sentiment of each unique GIF *j* (Unique GIFsentiment$_j$) daily by subtracting bearish from bullish declarations and dividing by the total appearances for GIF *j*, using a forward-expanding window to prevent look-ahead bias. This provides a continuous daily net bullish sentiment measure for each unique GIF. Table A1 presents examples of GIFs with the highest and lowest sentiment scores. Aggregate daily GIFsentiment is then the appearance-weighted average valence for all GIF-containing posts on a given day:

$$\text{GIFsentiment}_t = \sum_j \left(\frac{\#\text{Appearance}_{jt}}{\#\text{Posts}_t} * \text{Unique GIFsentiment}_{jt} \right), \quad (1)$$

where $\#\text{Appearance}_{j,t}$ is the total number of posts for GIF *j* on day *t*, $\#\text{Posts}_t$ is the total number of posts on day *t*, and $\text{Unique GIFsentiment}_j$ is the proportion of the net bullish sentiment declarations of GIF *j* on day *t*. A trading day is defined with a 4:00 p.m. cutoff, aggregating posts from 4:00 p.m. on day *t - 1* to 4:00 p.m. on day *t*. Calculating daily GIF-level sentiment allows for temporal variation, accommodating shifts in market context, meme culture, or user interpretation.

Temporal stability of GIF-level sentiment is assessed by examining the daily autocorrelation for a given GIF under varying minimum appearance thresholds. Table 1 Panel B

[13] The five-declaration threshold is broadly comparable to the use of five human raters in coding the sentiment of static Wall Street Journal images in Obaid et al. (2022).

shows that the average autocorrelation is 0.59 for GIFs with at least five appearances per day, rising to 0.79 for those with 25 or more. This demonstrates high temporal stability in GIF-level sentiment, particularly for frequently used GIFs.[14]

We hypothesize that GIFsentiment captures a unique dimension of investor behavior, distinct from sentiment conveyed through explicit textual declarations in non-GIF messages. Given the range of expressive formats chosen by Stocktwits users (GIFs only, bullish/bearish declarations only, both, or neither), we propose that users, as well as the posting contexts characterized by vivid, salient GIFs, exhibit a greater susceptibility to behavioral biases than those relying solely on textual sentiment declarations.

Supporting this distinction, Table A3 Panel A reveals that novice users with less trading experience and more susceptible to behavioral biases, are significantly more likely to post GIFs. In contrast, Panel B indicates that experienced users less frequently use GIFs, preferring explicit textual declarations of optimism or pessimism. This selective engagement suggests that GIF-derived sentiment is a stronger indicator of behavioral bias. To isolate behavioral effects, we also control for and compare GIFsentiment with SELFDEC, a declaration-based sentiment measure calculated exclusively from non-GIF postings.

2.3 Alternative sentiment measures

To evaluate GIFsentiment's incremental association with stock market outcomes, we control for various established sentiment measures. These include the Baker-Wurgler sentiment index (BW), the University of Michigan Consumer Sentiment Index (ICS), traditional media sentiment (MEDIAsentiment), textual sentiment from Stocktwits posts (TEXTsentiment), and self-declared sentiment from non-GIF Stocktwits posts (SELFDEC).

[14] To address potential serial correlation in residuals from autocorrelations in GIFsentiment and overlapping window returns in the return predictability regressions in Tables 4 onward, we adopt standard econometric corrections. These include using Nelson and Kim (1993) randomized *p*-values for the estimated coefficients and block bootstrapped standard errors. See discussion of Table 4 for further details.

The BW index, a monthly broad-based measure of speculative sentiment, is derived from a principal components analysis of six market-wide indicators described earlier. ICS is a monthly survey measure of consumer confidence about the economy and financial conditions, available from the University of Michigan's Surveys of Consumers or from the Federal Reserve Bank of St. Louis FRED (Federal Reserve Economic Data) website. Both BW and ICS are from the preceding month relative to the GIFsentiment score.

Drawing from the text-based sentiment literature,[15] we include MEDIAsentiment, a daily measure of traditional news media tone provided by RavenPack. RavenPack uses a proprietary machine learning model and AI to code sentiment from words in news articles.[16] We also control for two Stocktwits-derived text-related sentiment measures. The first, TEXTsentiment, is a daily aggregate textual sentiment measure calculated as the daily average of VADER scores applied to Stocktwits posts.[17] The second is SELFDEC, a daily measure of self-declared bullish or bearish sentiment from Stocktwits posts excluding GIFs. SELFDEC is defined as the net bullish declarations from *non*-GIF posts, divided by the total number of such posts daily. The study of Cookson and Niessner (2020) on investor disagreement and the study of Cookson, Engelberg, and Mullins (2023) on echo chambers use a similar self-declaration measure without regard to the presence or absence of GIFs and find that self-declarations predict individual stock returns or trading volumes.

[15] Sentiment measures have used the text of a Wall Street Journal column (Tetlock 2007), text from financial reports (Loughran and McDonald 2011), Google search terms (Da, Engelberg and Gao 2015), and text from the long-form social media platform Seeking Alpha (Chen et al. 2014). Renault (2017) and Giannini, Irvine, and Shu (2018) study the relationship of measures of text sentiment from short-form social media platforms—Stocktwits and Twitter respectively—with stock returns and trading volume.

[16] Studies that have used RavenPack's news article sentiment scores include Jeon, McCurdy, and Zhao (2022) and Bushman and Pinto (2024).

[17] Valence Aware Dictionary and Sentiment Reasoner (VADER) is a lexicon and rule-based sentiment analysis tool. It uses a pre-defined sentiment lexicon containing over 7,500 words, phrases, and emoticons. Each word is assigned a valence score reflecting its positive, negative, or neutral sentiment intensity. VADER then calculates the average sentiment score for a given text body, which in our analysis is the text words in postings. Hutto and Gilbert (2014) find that VADER performs better than other tools in the setting of microblog content on social media. Sohangir, Petty, and Wang (2018) apply VADER to StockTwits and find that it outperforms SentiWordNet and TextBlob in classifying bullish and bearish sentiment.

All six sentiment measures are standardized to have zero mean and unit variance for comparability. Table 2 Panel A presents their distribution prior to standardization, and Panel B reports their pairwise correlations. The measures exhibit moderate correlations, ranging from 0.16 to 0.49, suggesting shared underlying components, yet distinct aspects of investor sentiment. GIFsentiment correlates most strongly with TEXTsentiment, BW, and SELFDEC.

2.4 Evaluating sentiment measures with mood proxies

Growing research highlights the influence of mood on investor behavior, with several studies proposing empirical proxies for investor mood. We consider daily-level and monthly-level mood proxies. Daily mood is affected by environmental factors such as cloud cover. Hirshleifer and Shumway (2003) find that cloudy weather correlates with lower aggregate stock returns in tests across 26 countries, supporting a mood-based interpretation. Accordingly, we construct a daily cloud cover measure by averaging hourly NOAA[18] sky cloud cover data between 6 a.m. and 12 p.m. across national weather stations (Goetzmann et al. 2015; Edmans et al. 2022). To isolate mood-relevant fluctuations from other seasonally varying effects, we de-seasonalize the cloud cover series by subtracting each week's average cloudiness from its corresponding daily values following Hirshleifer and Shumway (2003).

We also include a daily COVID-19 stringency index to capture mood variation from policy-induced psychological stress. Past research shows that pandemic restrictions adversely impacted population mood (Terry et al. 2020; Bueno-Notivol et al. 2021; Edmans et al. 2022). We construct this index from lockdown restrictions compiled by the University of Oxford's COVID-

[18] National Oceanic and Atmospheric Administration (NOAA) provides local climatological data from over 1,000 weather stations. Each weather station records the degree of cloud cover, which takes on integer values of 0 (clear – no coverage), 1 (few – 2/8 or less coverage), 2 (scattered – 3/8-4/8 coverage), 3 (broken – 5/8-7/8 coverage), or 4 (overcast sky – 8/8 coverage).

19 government response tracker.[19]

At the monthly level, we incorporate calendar seasonality in mood, drawing on psychological and behavioral finance literature. For the United States, January and March are associated with optimism and SAD (seasonal affective disorder) recovery, respectively, while September and October are associated with SAD onset and diminished mood. Accordingly, we define a positive mood indicator for January and March, and a negative mood indicator for September and October (e.g., Thaler 1987 on positive mood in January; Kamstra et al. 2017 and Hirshleifer, Jiang, and DiGiovanni 2020 on positive mood in January and March, and negative mood in September and October).

To evaluate GIFsentiment as a mood proxy, we examine its association with established daily and monthly mood proxies. We compute correlations between GIFsentiment and weather-induced mood shifts, COVID-related restriction stringency, and seasons associated with mood variations. Parallel analyses using TEXTsentiment, SELFDEC, BW, ICS, and MEDIAsentiment benchmark the strength and uniqueness of the GIF-based construct.

Table 3 Panels A and B present the Pearson correlation estimates. Consistent with GIFsentiment capturing investor mood, Panel A Column 1 shows that GIFsentiment is negatively correlated with daily cloud cover (DCC) and COVID-related restriction stringency (ΔCOVID Index). Panel B Column 1 further reveals a negative association with Negative Months (September and October). For comparison, Columns 2 to 6 in Table 3 Panels A and B present correlations for the five alternative sentiment measures with the same mood proxies. (Since BW and ICS are monthly measures, their correlations are estimated at the monthly level using aggregated mood proxies.) These alternatives generally lack consistent, expected associations with mood proxies.

[19] Available from https://github.com/OxCGRT/covid-policy-tracker/tree/master/data.

Specifically, TEXTsentiment is negatively correlated with uplifted mood periods, contrary to expectations, and uncorrelated with DCC or ΔCOVID Index. SELFDEC and ICS are negatively correlated with the ΔCOVID Index, but not Positive Months, Negative Months, or DCC. While BW correlates with all four mood proxies in the predicted directions, none of the correlations are statistically significant. MEDIAsentiment has a positive correlation with DCC, contrary to expectations.

The inconsistent associations of these five established sentiment measures with mood variables are puzzling. This raises the question of what these sentiment measures actually capture. Some past studies suggest that textual sentiment measures may reflect fundamental news rather than purely reflecting investor mood (e.g., Tetlock 2007; Loughran and McDonald 2011).

To examine this possibility, we examine the relation between all six sentiment measures with economic fundamentals. While not strictly required, a low correlation with fundamentals suggests a purer proxy for sentiment-driven investor attitudes, as distinct from rational reactions to news. We use %PositiveEANews as a fundamental news proxy, defined as the percentage of earnings announcements that meet or exceed consensus analyst forecasts for cashtag-mentioned firms. Table 3 Panel C indicates that SELFDEC, ICS, and MEDIAsentiment are positively associated with %PositiveEANews at the 1% or 5% level, suggesting that they capture fundamental information rather than just behavioral sentiment. In contrast, GIFsentiment and BW show no significant correlation with this fundamentals proxy. Taken together, the evidence in Panels A and B indicates that GIFsentiment, a visual, user-generated construct, more purely reflects mood-driven sentiment as contrasted with rational responses to fundamental news.

2.5 Evaluating GIF sentiment using a GPT vision model

We further cross-validate GIFsentiment as a sentiment proxy using an alternative visual sentiment measure, OpenAI's GPT-4V vision-language model, to independently code GIF sentiment. Owing to the computational costs, we restrict this exercise to the top 1 % of GIFs ranked by total appearance count prior to November 2023. This selection strategy enhances representativeness by prioritizing frequently used GIFs over those appearing sporadically. It also mitigates look-ahead bias by excluding data potentially influenced by GPT-4o, a newer model publicly released in November 2023.

For this subset, we prompt GPT-4V to assign a continuous sentiment score ranging from −1 (strongly negative) to +1 (strongly positive) for each unique GIF. Each GIF receives a single score reflecting its overall emotional valence. We then calculate the correlation between this GPT-coded sentiment (GPT4V-GIFsentiment) and our self-declaration-based sentiment measure GIFsentiment. In addition to the continuous measure, we also construct binary sentiment indicators (−1 for negative sentiment score < 0, and +1 for positive sentiment score > 0) for both measures.

Table A3, Panel C, reports a correlation of 0.485 ($p < 0.01$) correlation between continuous GIFsentiment and GPT4V-GIFsentiment, with the binary indicators showing an even stronger correlation of 0.814 ($p < 0.01$). These findings indicate a high consistency of our GIFsentiment measure with a proxy for sentiment based upon an advanced vision-language model.

3 GIF Sentiment and Stock Returns

3.1 GIF sentiment association with stock market returns

This section examines the relation between GIFsentiment with contemporaneous daily returns on the aggregate CRSP value-weighted S&P 500 market index, SPX, and the ability of GIFsentiment to forecast future daily returns over the subsequent week and month. We analyze GIFsentiment individually and alongside five other sentiment measures to assess its incremental

explanatory power. Investor sentiment theory posits that net positive sentiment is associated with positive short-term returns but predicts negative long-term underperformance as mispricing corrects. We run the following regression:

$$\%\text{Ret}_{(t+m,t+n)} = \alpha + \beta\ \text{Sentiment}_t + \gamma\ \text{Controls}_t + \varepsilon_t, \quad (2)$$

where $\%\text{Ret}_{(t+m,t+n)}$ represents contemporaneous day t, one-week ($t + 1$, $t + 5$), and one month ($t + 1$, $t + 20$) cumulative SPX returns. Sentiment_t is GIFsentiment_t in the individual regressions, or a vector including also TEXTsentiment, SELFDEC, BW, ICS, and MEDIAsentiment in joint regressions (β vector in that case). All sentiment measures are standardized to have zero mean and unit variance for comparability. [20] Behavioral theory predicts a positive coefficient for contemporaneous returns and negative coefficients for subsequent weekly and monthly returns.

Following past studies (Da et al. 2014; Edmans et al. 2022), we control for EPU, a daily news-based measure of U.S. economic policy uncertainty (Baker, Bloom, and Davis 2016),[21] ADS, a U.S. macroeconomic activity index from the Federal Reserve website (Aruoba et al. 2009),[22] past returns, %Ret[-5, -1] and %Ret[-21, -6], to account for potential return reversals, daily Log#EA, the logarithm of the number of earnings announcements, for investor distraction by fundamental events (Hirshleifer and Teoh 2003), and the daily abnormal number of posts on Stocktwits (Cookson, Lu, Mullins, and Niessner 2024) for general social media attention.

To address potential serial correlation in sentiment measures, randomized *p*-values are calculated using the Nelson and Kim (1993) procedure and reported in all the tests in the main tables throughout the paper. For the weekly and monthly returns predictability tests, these

[20] The Variance Inflation Factor (VIF) values, ranging from 1.5 to 2, indicate that multicollinearity is not a concern.
[21] This measure is constructed by counting the number of U.S. newspaper articles achieved by the NewsBank Access World News database with at least one term from each of the following three categories: (i) "economic" or "economy"; (ii) "uncertain" or "uncertainty"; and (iii) "legislation," "deficit," "regulation," "congress," "Federal Reserve," or "White House." Baker et al. (2016) provide evidence that EPU captures perceived economic policy uncertainty. The data are available at https://www.policyuncertainty.com/index.html.
[22] This index extracts the latent state of macroeconomic activity from many macroeconomic variables (jobless claims, payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real gross domestic product) using a dynamic factor model. The data are available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads.

dependent variables have overlapping windows, which may induce serial correlation in the residuals. To address this concern, we re-estimate the return regressions using the moving block bootstrap method. We report the robustness tests corresponding to the Table 4 tests in Table A8 using both a small block size (n = 10) and a large block size (n = 30).[23] The smaller block size yields more resamples but captures less of the dependence structure, while the larger block size better preserves dependence but results in fewer effective resamples and thus higher variance of the bootstrap standard errors. Table A8 shows robustness of results for either bootstrap block size.

Table 4 Panel A reports results for the separate regressions of the returns on the Standard and Poor 500 Index (SPX) returns contemporaneously, one week following, and one month following the conditioning date on GIFsentiment and controls. GIFsentiment is associated positively with contemporaneous aggregate market returns and negatively with the subsequent one-week and one-month returns after controlling for fundamentals EPU, ADS, lagged returns, Log#EA, and Log#AbnMessages. The negative predictive power of GIFsentiment for future returns is consistent with GIFsentiment capturing mispricing rather than fundamental information. The estimated coefficients on the control variables are reasonable or as expected.

The economic magnitudes of the GIFsentiment coefficients are substantial. A one standard deviation increase in GIFsentiment is associated with a 20 basis points (bp) increase in same-day market returns, followed by a 23.5 bp lower return in the following week or 106.8 bp lower return in the following month. This monthly reversal annualizes to −13.5%, a substantial economic magnitude.

The magnitude of the subsequent correction exceeds the contemporaneous reaction. This is plausible in a behavioral context where high sentiment at a given date is associated with preexisting overpricing as well as a new increment to mispricing at the focal date. Untabulated results further indicate that GIFsentiment positively correlates with prior week returns, consistent

[23] We have performed these robustness tests for the later tables as well.

with sentiment persistence and associated mispricing. We address potential serial correlation concerns through standard adjustments and robust *p*-values from randomization and bootstrapping procedures.

Panel B confirms that the relationship of returns with GIFsentiment is robust even after controlling for other sentiment proxies. A one-standard-deviation higher GIFsentiment is associated with a 14.1 bp higher same-day return ($p = 0.02$) and an 87.5 bp lower return over the subsequent month ($p < 0.01$). This sustained explanatory and forecasting power indicates that GIFsentiment is a strong incremental proxy for identifying past market overvaluation that corrects within a month.

Unlike GIFsentiment, most other sentiment proxies, except for MEDIAsentiment in Panel B, do not display incremental return patterns consistent with investor sentiment theory. For instance, TEXTsentiment and SELFDEC are positively associated with contemporaneous (day 0) returns, but they do not significantly negatively predict future one-month returns, as expected under mispricing correction. BW and ICS are negatively associated with day 0 returns, contrary to sentiment theories, potentially owing to low power for a monthly sentiment measure. Furthermore, TEXTsentiment and SELFDEC positively predict long-horizon returns, suggesting that they may capture long-term fundamentals information rather than transient mispricing. Overall, these findings indicate that GIFsentiment aligns more strongly with behavioral predictions, serving as a more effective proxy for investor sentiment.

3.1.1 Positive vs negative GIF sentiment

While many past sentiment measures focus on pessimism and negative market outcomes (Tetlock 2007; Chen et al. 2014; Da, Engelberg and Gao 2015; Obaid and Pukthuanthong 2022), high-arousal positive content is more likely to go viral (Berger and Milkman 2012). Social media users are more likely to upvote or retransmit positive messages (Kramer, Guillory, and Hancock 2014; Rosenbusch, Evans, and Zeelenberg 2019; Goldenberg and Gross 2020).

To separately explore the ability of GIFs to capture optimism versus pessimism, we construct separate positive and negative aggregate GIFsentiment measures from unique GIFs. Here, PositiveGIFsentiment is constructed as in Equation (1) using only GIFs with positive sentiment, and NegativeGIFsentiment is constructed using only GIFs with negative sentiment. So, if there is no asymmetry of effect, we would expect the coefficients on PositiveGIFsentiment and on NegativeGIFsentiment to match the coefficient on GIFsentiment in the basic tests. A higher coefficient on PositiveGIFsentiment versus NegativeGIFsentiment would be indicative that one effect is asymmetrically stronger than the other.

Table 5 presents the predictability of returns from PositiveGIFsentiment from net positive GIFs and NegativeGIFsentiment from net negative GIFs. Panel A shows both proxies predict returns in the predicted directions when included in regression Equation (2).

Notably, NegativeGIFsentiment predicts negative returns within one week, while PositiveGIFsentiment negatively predicts returns over a longer horizon, typically over a month. The gradual diffusion and accumulation of high-arousal positive content (Berger and Milkman 2012; Kramer, Guillory and Hancock 2014; Rosenbusch, Evans, and Zeelenberg 2019; Goldenberg and Gross 2020), would delay reversal for optimistic sentiment relative to negative sentiment.

Panel B shows that with all six sentiment measures included in the regressions, the coefficient on PositiveGIFsentiment remains consistent with our main finding. In contrast, NegativeGIFsentiment is positively associated with day 0 returns but does not exhibit future return reversals. This suggests that its mood component may overlap or be subsumed by other sentiment measures included in the regression specification.

3.1.2 Intraday analysis

A caveat to our daily stock return analysis is the relatively short sample period, from September 1, 2020 to the end of 2024. This limits sample size, reducing statistical power. To

partially address this, we investigate intraday GIFsentiment variation. For the intraday analysis, GIFsentiment, TEXTsentiment, and SELFDEC are constructed at 30-minute intervals. BW, ICS, and MEDIAsentiment, however, remain at their daily or monthly frequencies owing to data constraints. We examine the association of intraday sentiment with the SPY ETF returns from the TAQ database over three windows: (i) contemporaneous 30-minute interval (ii) short-term forward ($t + 30$ minutes to $t + 1$ day) and (iii) short-term forward ($t + 30$ minutes to $t + 2$ days).

Table 6 presents the results. Panel A indicates that 30-minute GIFsentiment is positively associated with contemporaneous returns ($p < 0.01$) and higher GIFsentiment predicts negative returns over the subsequent one to two days. Panel B, with additional sentiment controls, indicates GIFsentiment continues to negatively predict returns over the following two days. These findings are consistent with our earlier analysis using daily GIFsentiment, supporting the robustness of main results against sample size or estimation instability concerns.

3.1.3 Robustness tests

We perform several robustness checks to ensure our main inferences are not influenced by outliers in returns or GIFsentiment, or sensitive to the market index. These include: (i) Winsorizing returns at the top and bottom 1%, 5%, and 10% levels; GIFsentiment remaining robust (Table A4). (ii) Constructing GIFsentiment using only GIFs exceeding the 50th or 75th percentile of cumulative appearances, also yielding consistent results (Table A5). (iii) Excluding days with high DFBETA influence (absolute DFBETA > $2/\sqrt{n}$,); GIFsentiment coefficients yield similar results (Table A6). (iv) Excluding the initial three months GIF adoption period (2020Q3 to 2020Q4) on Stocktwits when GIF usage likely took time to gain traction, to mitigate concerns about anomalous early adoption patterns; results remain consistent (Table A7).

Overall, our findings are robust to outliers and early adoption platform dynamics. Furthermore, untabulated results confirm that daily GIFsentiment-return relations are robust across all five stock indices: the CRSP value-weighted index (VWRETD), the SPDR S&P 500 (SPY),

the PowerShares QQQ Trust (QQQ) for the portfolio of innovation stocks, the Russell 100 Index ETF (IWB), and the Russell 2000 Index ETF (IWM). This shows that the predictive power of GIFsentiment holds across indices with varying size and sector compositions.

3.2 GIF sentiment and susceptibility to mispricing

Investor sentiment theory predicts that the return forecasting power of a sentiment proxy is stronger for portfolios of stocks with greater mispricing pressure or tighter limits to arbitrage. Specifically, we test examine the association of GIFsentiment with immediate and long-term returns across stock portfolios that differ in firm size and idiosyncratic uncertainty. High uncertainty amplifies individual investor biases (Kumar 2009), while tighter limits to arbitrage increase mispricing (Pontiff 1996; Shleifer and Vishny 1997). Small stocks, being riskier, more costly to arbitrage, and disproportionately held by retail investors, are particularly prone to mispricing (Lee, Shleifer and Thaler 1991).

Motivated by these insights, we test whether the sensitivity of relationship between contemporaneous and future returns of stock index portfolios with GIFsentiment differs across portfolios that differ in these characteristics. To do so, we first stocks into market capitalization quintiles. Consistent with past research showing stronger sentiment-return associations for smaller stocks (e.g., Baker and Wurgler 2006, Edmans, Garcia, and Norli 2007), we expect stronger GIFsentiment return reversals in the small-stock quintile.

Next, we sort stocks into quintiles based on two risk measures: idiosyncratic volatility from Fama-French five-factor model residuals over the prior 36-months and total return volatility (Wurgler and Zhuravskaya 2002). We hypothesize a stronger association between GIFsentiment and returns among portfolios with higher idiosyncratic or total return volatility (Wurgler and Zhuravskaya 2002, Baker and Wurgler 2006).

To test these hypotheses, we estimate Equation (2) for subsamples based on firm size, idiosyncratic volatility, and total return volatility. We consider (1) the Small Cap (bottom quintile)

and Large Cap (top quintile) groups; (2) High and Low idiosyncratic risk groups (top and bottom quintiles) and (3) HighVol and LowVol groups (top and bottom total return volatility quintiles). Table 7 reports these results.

Table 7 Panel A1 presents results for Small Cap (Columns 1-3) and Large Cap (Columns 4-6). GIFsentiment is positively associated with same-day returns and negatively predicts subsequent one-month returns for both groups, consistent with behavioral bias. Furthermore, Small Cap stocks exhibit larger magnitudes for both the contemporaneous positive returns and the negative one-month reversals. The last row in Panel A1 show significant p-values of 1% or less for the coefficient differences between large and small caps for these two windows, confirming that smaller stocks are more sensitive to sentiment-driven mispricing.

Panel A2 indicates that the predictive power of GIFsentiment is robust even after controlling for alternative sentiment proxies. A one-standard-deviation increase in GIFsentiment is associated with a 10.3 bp higher day 0 return and a 108.5 bp lower return over the subsequent month for the Small-Cap group relative to the Large-Cap group. This confirms that the relation of aggregate GIF sentiment to returns is more pronounced among smaller stocks.

Panels B1 and B2 compare the associations of GIFsentiment with returns for High (Columns 1-3) and Low (Columns 4-6) idiosyncratic volatility stocks. Estimates indicate a more pronounced association between GIFsentiment and both same-day and one-month-ahead returns for High volatility stocks. Coefficient differences across the two groups have *p*-values at 1% or less.

Panels C1 and C2 show similar patterns for firms grouped by total return volatility. Specifically, High Volatility stocks (top quintile) exhibit significant higher same-day returns and lower returns over the subsequent month compared to Low Volatility stocks (bottom quintile).

3.3 GIF sentiment and stock market volatility

Theoretical models predict that investor sentiment and noise trading increase the volatility

of asset prices (Black 1986, De Long et al. 1990). For example, investors trading based on noise induce random deviations from fundamentals. To investigate this, we estimate the association between absolute GIFsentiment and stock market volatility. Absolute GIFsentiment is used because extreme sentiment (either high or low) can motivate heavy trading. Return volatility (%) is measured as the standard deviation of daily S&P 500 index returns over windows: from day 0 through 5, and from day t through $t + 20$, aligning with the windows in our return tests. We estimate the following regression:

$$\%\text{Volatility}_{[t,t+n]} = \alpha + \beta\,|\text{Sentiment}_t| + \gamma\,\text{Controls}_t + \varepsilon_t, \quad (3)$$

where Controls include the previous control variables and one-week-lagged stock market volatility.

Table 8 reports the results. Absolute GIFsentiment at day t positively correlates with return volatility in the subsequent week ($t + 1$ to $t + 5$). In Column 1, a one-standard-deviation increase in absolute GIFsentiment corresponds to a 0.047 higher stock market volatility. This represents 9% of the weekly volatility standard deviation of 0.524.[24] Results strengthen in Column 2 when controlling for other sentiment proxies. The association between absolute GIFsentiment and subsequent one-month ($t + 1$ to $t + 20$) return volatility in Columns (3) and (4) is marginally significant at the 5% level. This result is not surprising, given our return tests indicate stock price decline after day t, which may reduce longer-horizon volatility.

Absolute TEXTsentiment and absolute SELFDEC at day t are negatively correlated with stock market volatility over the subsequent week and month. These negative associations suggest these measures provide fundamental information that resolves some uncertainty, reducing future uncertainty.

Overall, our return volatility findings consistently suggest that visual-based GIFsentiment captures investor mood or attention-induced biases in expectations, leading to deviations of stock

[24] The magnitude is similar to that in Edmans et al. (2022). A one-standard-deviation increase in their music sentiment is associated with a 3.7 bps increase in stock market volatility, or 3.48% of the average weekly volatility of 1.06.

price from fundamentals and to excess volatility. In contrast, TEXTsentiment and SELFDEC appear to reflect fundamental information more than mood.

4 GIF Sentiment, GIF Disagreement, and Trading Activity

4.1 GIF sentiment and total trading volume

Behavioral models propose that sentiment shocks induce disagreement between rational and noise investors, increasing trading activity (De Long et al. 1990, Campbell et al. 1993). If GIFsentiment reflects these dynamics, we expect extreme sentiment (high or low) to correlate with increased trading volume as the market absorbs these orders.

We test the association of GIFsentiment with market trading. Intraday level analysis is employed to enable more granular and timely examination of market reactions and their temporal alignment with sentiment shocks.

Table 9 examines the relation between aggregated 30-minute SPY trading volume and GIFsentiment. Following Tetlock (2007), we run the following regression:

$$\text{LogTotalVol}_{t+m\to t+n} = \alpha + \beta\,|\text{Sentiment}_t| + \delta\,\text{Controls}_t + \varepsilon_t, \quad (4)$$

where LogTotalVol represents the natural logarithm of one plus total SPY trading volume, cumulated within a given 30-minute interval *t*, and over subsequent one and two-day windows from *t* + 30 minutes to *t* + 1 day and from *t* + 30 minutes to *t* + 2 days respectively. $|\text{Sentiment}_t|$ is the standardized absolute value of GIFsentiment with mean of zero at 30-minute interval *t*, where high values indicate unusually strong positive or negative sentiment within that window.

Table 9 Panel A Columns 1 to 3 show positive coefficients for $|\text{Sentiment}_t|$ on the contemporaneous 30-minute interval *t*, over the next day (*t* + 30m to *t* + 1d), and over the second next day (*t* + 30m to *t* + 2d). This indicates both high and low GIFsentiment levels are associated with higher trading volume. A one-standard-deviation increase in GIFsentiment corresponds to 0.162 higher log trading volume contemporaneously, a 6.1% of its standard deviation (2.67), and

0.036 and 0.034 higher log volume over the subsequent week and month (2.5 and 2.3% of their standard deviation) respectively. Results are qualitatively similar when controlling for the five additional sentiment measures.

4.2 GIF disagreement and total trading volume

Belief heterogeneity models posit that disagreement among investors from differing expectations drives trading activity (Harrison and Kreps 1978; Kandel and Pearson 1995). Consistent with this, we test if GIFsentiment disagreement, measured as the dispersion or imbalance in bullish versus bearish declarations, correlates with increased trading volume. If GIFsentiment captures meaningful variation in investor beliefs, greater GIFsentiment disagreement should signal heightened divergence in expectations, resulting in higher trading volume.

Following Cookson and Niessner (2020), we construct a measure of disagreement in GIF sentiment at each 30-minute interval as:

$$\text{GIFDisagreement}_t = \sqrt{1 - \text{GIFSentiment}_t^2}, \quad (5)$$

where GIFSentiment_t^2 is the square of the average GIF sentiment within the 30-minute interval *t*. This transformation captures the idea that disagreement is highest when sentiment is evenly split between bullish and bearish and is lowest when strongly concentrated in one direction. This measure captures sentiment divergence at the 30-minute frequency.

We estimate Equation 4 from Section 4.1 replacing $|\text{Sentiment}_t|$ with GIFDisagreement_t and retaining the same controls. Table 9 Panel B presents these results. Columns 1-3 show positive $\text{GIFDisagreement}_\text{t}$ coefficients ($p < 0.01$), indicating that greater divergence in sentiment is associated with higher trading volume. This finding supports the interpretation that GIFsentiment captures meaningful heterogeneity in investor beliefs, where heightened disagreement corresponds to more active market participation.

5 GIF Sentiment and Fund Flows

If sentiment is associated with investor decisions, we expect to observe corresponding patterns in mutual fund investing. This consideration can be important because individual investors hold about 95% of long-term U.S. mutual fund total net assets (Investment Company Institute 2023). Since daily fund flows aggregate to the asset-class (Ivković and Weisbenner 2009), we investigate the predictive power of GIFsentiment for daily mutual fund flows between two asset classes, U.S. equities versus U.S. bonds. We test the flight-to-safety hypothesis, which predicts that investors move from risky (equities) to safe assets (bonds) when investor sentiment is low, and conversely from bonds to equities when sentiment is high (Baker and Wurgler 2012, Da et al. 2015, Edmans et al. 2022).

Our daily equity and bond fund flow data are from EPFR Global, a private company that tracks performance and asset allocation of equity and debt mutual funds in developed and emerging markets.[25] Daily flows are computed as the ratio of dollar flow to fund total net assets (TNA). We estimate the following regression:

$$Y_{t+m \to t+n} = \alpha + \beta\ \text{Sentiment}_t + \gamma\ \text{Controls}_t + \varepsilon_t, \tag{6}$$

where Y = EFF or BFF, which represent deseasonalized daily net equity and bond fund flows, respectively, scaled by TNA. Controls are as previously defined. To remove seasonality, equity and bond fund flows are first regressed on day-of-week and month-of-year indicators, with the residuals used as the dependent variables in Equation (6). Table 10 Panel A reports equity fund flow results and Panel B bond fund flow results.

Panel A shows that GIFsentiment is positively correlated with equity fund flows (EFF) on day 0 and the subsequent week on days $t + 1$ to $t + 5$. Results remain similar after including the five additional sentiment measures. A one-standard-deviation higher GIFsentiment is associated with 0.037 higher EFF on day 0 (9.5% of day 0 EFF standard deviation), and 0.002 higher EFF

[25] As of 2024, EPFR global tracks over 151,000 equity share classes and 50,000 individual bonds, comprising more than $55 trillion in assets in developed, emerging and frontier markets (EPFR Product Overview 2024).

during the subsequent week (8.8% of its EFF standard deviation).

Panel B shows that GIFsentiment is negatively correlated with bond fund flows (BFF) on day 0 and during $t + 1$ to $t + 5$. With the five additional sentiment measures, GIFsentiment is unrelated to day 0 BFF but remains negatively correlated with subsequent week (days $t + 1$ to $t + 5$) BFF. A one-standard-deviation higher GIFsentiment corresponds to a 0.037 lower BFF on day 0 (9.3% of its standard deviation) and a 0.006 lower BFF during the subsequent week (19.8% of its standard deviation). In summary, high GIFsentiment forecasts inflows to equity funds and outflows from bond mutual funds in the subsequent week.

TEXTsentiment shows no association with equity fund flows. SELFDEC, however, is associated with greater flight towards bond mutual funds. Overall, our findings suggest higher GIFsentiment is associated with flight away from safety, a pattern not observed for high TEXTsentiment or high SELFDEC.

6 Conclusion

Investor sentiment is shaped by both individual reactions to traditional news media and social interactions among investors. So a comprehensive understanding of investor sentiment requires studying the communication dynamics between investors. A key window for such study is provided by data on behavior in social media platforms. Research in psychology and social media has emphasized the importance of multimodal communications, and especially to the expressive and attention-directing properties of dynamic visual content. This paper proposes a novel measure of investor sentiment derived from dynamic visuals, GIFs, shared by users on the social media platform Stocktwits.com.

Our daily measure of aggregate investor sentiment, GIFsentiment, is correlated with established exogenous mood proxies from past literature. Importantly, GIFsentiment is positively correlated with contemporaneous aggregate stock market returns and negatively predicts future market return at horizons of up to one month. GIFsentiment also predicts stock market volatility,

retail trading activity, and a flight from safety, i.e., from bonds to equities. The return reversal pattern is consistent with transient sentiment-induced mispricing (De Long et al. 1990, Campbell et al. 1993).

Our findings are robust to controlling for various sentiment proxies, including social media proxies such as self-declared sentiment and textual sentiment of postings; Baker-Wurgler sentiment; Michigan Consumer sentiment; and traditional mass media sentiment. They also hold when controlling for fundamentals such as U.S. economic policy uncertainty, U.S. macroeconomic activity, and past returns.

Consistent with investor sentiment and market mispricing predictions, the associations of GIF sentiment with returns are strongest for portfolios of small stocks and high idiosyncratic volatility stocks. These portfolios are usually viewed as more sensitive to retail investor misperceptions and costlier to arbitrage.

We find sharp differences between results for GIFsentiment and two alternative sentiment proxies, TEXTsentiment and SELFDEC sentiment. GIFsentiment outperforms both these sentiment measures in forecasting aggregate market return reversals. Unlike the return reversals predicted by GIF sentiment, TEXTsentiment and SELFDEC positively predict returns in both the short and long run. This sharp contrast likely reflects that dynamic visuals heavily capture emotion- or attention-driven biases in investor expectations, whereas text and user declarations reflect at least some meaningful fundamental information.

Our approach to measuring the sentiment of dynamic visual content analysis benefits from the large sample of Stocktwits.com participants who directly label the sentiment of their posts. Since participants on this platform have a strong interest in the stock market, our sentiment proxy is based on an ecologically relevant investment context as compared with the use other types of raters for estimating sentiment.

Our analysis of social media sentiment differs from most past studies aggregate market

return predictability in predicting reversals at high frequencies. Most past studies identify reversals in aggregate market returns at long time horizons of up to several years (Fama and French 1988, Poterba and Summers 1988). In contrast, GIF sentiment predicts negative aggregate market returns at daily to weekly frequencies.

In conclusion, this paper is the first to study GIFs, a type of dynamic visual representations, as a means of communicating ideas about stock investing with other investors. It exploits both dynamic visuals and textual information to construct a high-frequency (daily) market sentiment measure that predicts aggregate stock market returns and other aggregate market outcomes. As such, the paper contributes new insights about investor sentiment, stock market return predictability, social media in financial markets, and the growing field of social economics and finance.

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Figure 1
The Trend of GIF Postings on Stocktwits Over Time

This figure plots the time trend of GIF postings on Stocktwits from September 1, 2020, to October 31, 2024. Beginning on September 1, 2020, Stocktwits started supporting GIFs posted from all users' accounts.

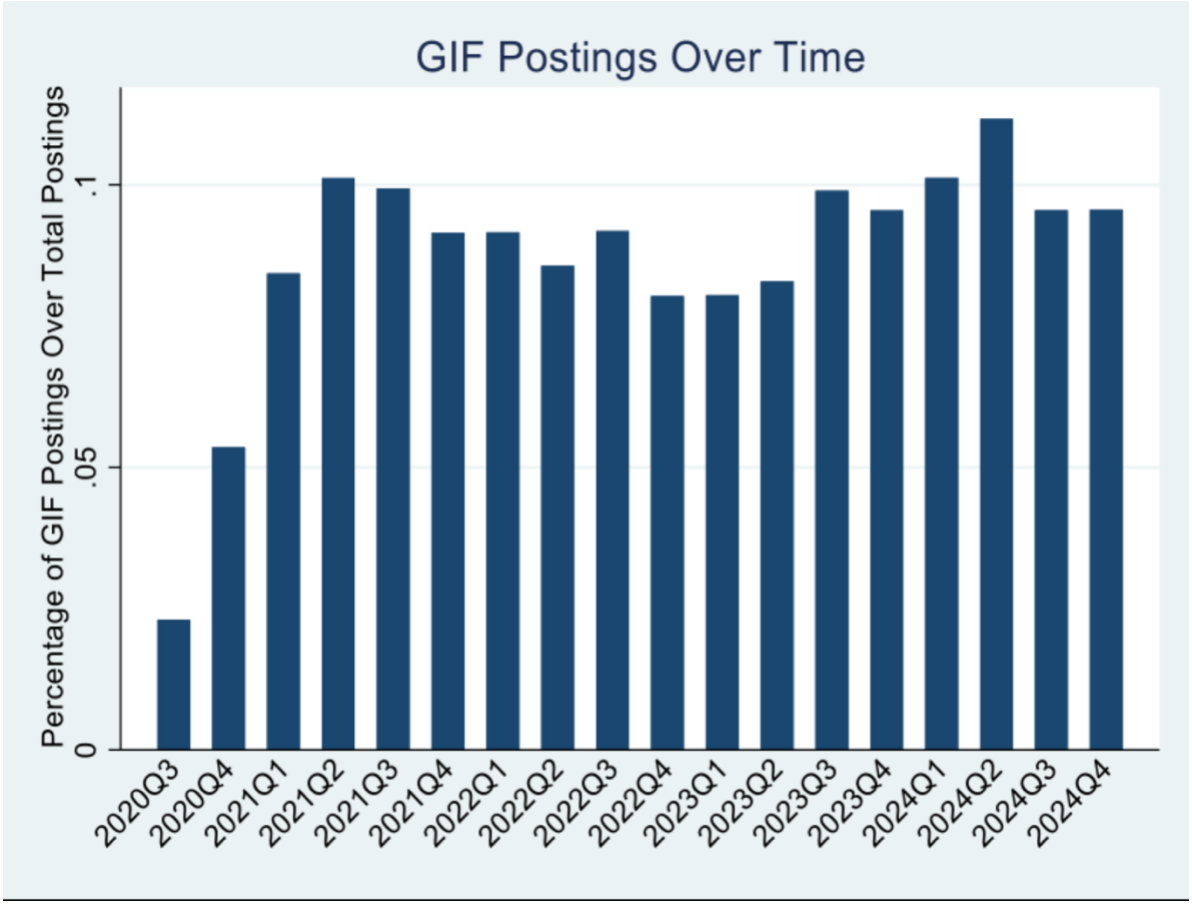
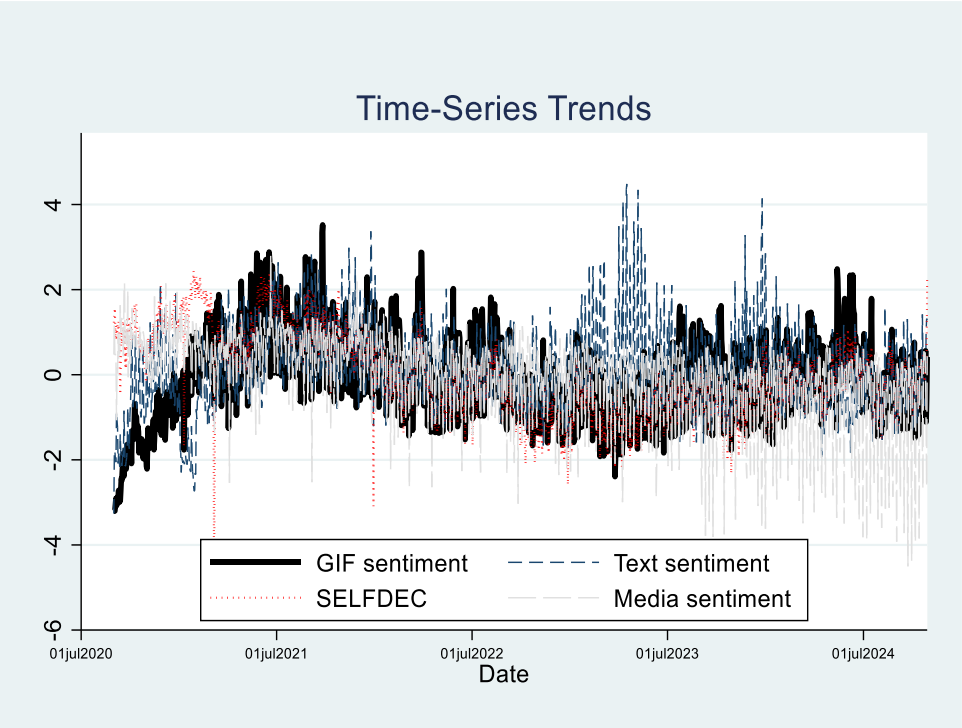


Figure 2
The Time Series of Alternative Sentiment Measures

Panel A shows the time series of daily GIF sentiment, SELFDEC, Text sentiment, and Media sentiment for our sample period between September 1, 2020, and October 31, 2024. Panel B shows the time series of monthly GIF sentiment, BW sentiment, and ICS for our sample period.

Panel A Time-Series of Daily Sentiment Measures



Panel B Time-Series of Monthly Sentiment Measures

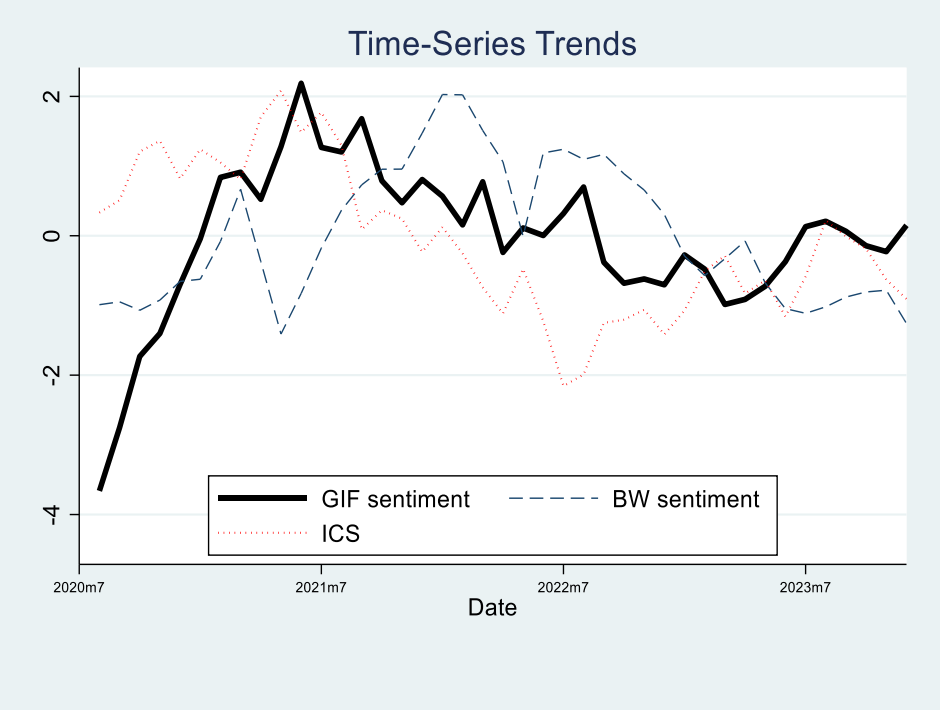


Table 1
GIF and Bullish/Bearish Self-Declarations

Panel A presents the distribution of the number of bullish declarations (#Declared_Bullish), bearish declarations (#Declared_Bearish), and the frequency of each unique GIF (#Appearance) at the GIF-day level. These statistics are calculated using only information available at the daily level to avoid look-ahead bias. Panel B reports the autocorrelation statistics of GIFsentiment, conditional on different minimum appearance thresholds, to assess its temporal persistence across GIFs with varying levels of appearances.

Panel A: Distribution of Bullish and Bearish Declarations at Daily-GIF Level for All GIFs

Variable (N= 4,121,312)	Mean	Std Dev	p10	p25	p50	p75	p90
#Declared_Bullish	127.57	452.96	1	3	15	74	268
#Declared_Bearish	16.15	76.81	0	0	1	6	28
#Appearance	184.35	582.64	1	5	25	123	424

Panel B: Autocorrelation of GIF Sentiment

#Appearance	N	Mean	Std Dev	P10	P25	P50	P75	P90
>=5	94,884	0.59	0.39	0.01	0.43	0.72	0.88	0.95
>=10	59,799	0.69	0.30	0.25	0.57	0.79	0.91	0.96
>=25	23,834	0.79	0.21	0.51	0.72	0.86	0.94	0.97

Table 2
Summary Statistics

Panel A reports the summary statistics for GIFsentiment, TEXTsentiment, self-declared sentiment (SELFDEC), Baker-Wurgler sentiment index (BW), consumer sentiment index (ICS), news media sentiment (MEDIAsentiment), and the daily returns on the CRSP S&P 500 Index (SPX). Panel B reports the pairwise Pearson correlations between the sentiment measures. GIFsentiment is calculated following Equation (1) in the text. All variable definitions are in Table A2.

Panel A: Summary Statistics of Main Variables

Variable	N	Mean	Std Dev	P10	P25	P50	P75	P90
GIFsentiment	1,045	0.05	0.01	0.03	0.03	0.04	0.05	0.06
TEXTsentiment	1,045	0.09	0.02	0.06	0.07	0.08	0.09	0.10
SELFDEC	1,045	0.28	0.08	0.15	0.17	0.22	0.27	0.34
BW	858	0.78	0.78	-0.24	-0.12	-0.03	0.89	1.25
ICS (consumer index)	1,045	69.44	9.03	56.70	58.40	62.80	68.20	76.90
MEDIAsentiment	1,045	0.11	0.04	0.05	0.06	0.08	0.11	0.14
SPX	1,045	0.05	1.06	-1.70	-1.20	-0.51	0.07	0.70

Panel B: Pearson Correlations Between Sentiment Variables

	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
GIFsentiment	1					
TEXTsentiment	0.45	1				
	<.0001					
SELFDEC	0.49	0.11	1			
	<.0001	0.00				
BW	0.47	0.34	0.26	1		
	<.0001	<.0001	<.0001			
ICS	0.16	-0.04	0.60	0.02	1	
	<.0001	0.20	<.0001	0.57		
MEDIAsentiment	0.16	0.17	0.53	0.34	0.33	1
	<.0001	<.0001	<.0001	<.0001	<.0001	

Table 3
Correlation Between Sentiment Measures and Mood Proxies

Panel A reports the Pearson correlation of sentiment measures and **daily** mood proxies. DCC is the average daily cloud cover, deseasonalized by each week's average cloud cover. ΔCOVID Index is the change in daily containment and closure index. Panel B reports the Pearson correlation of sentiment measures and **monthly** mood proxies. Positive months is an indicator variable that equals 1 in January and March and 0 otherwise. Negative months is an indicator variable that equals 1 in September and October and 0 otherwise. Panel C reports the results of regressing alternative sentiment measures on an information proxy, %PositiveEANews, measured by the percentage of earnings news that meet or beat analyst consensus forecast on the announcement date. GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. BW and ICS sentiment measures are monthly measures so all correlations with BW and ICS are estimated monthly. The other variables in other columns are daily. All sentiment measures are standardized to have zero mean and unit variance. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: The Pearson Correlation Between Sentiment Measures and Daily Mood Proxies

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
DCC	-0.118***	-0.047	-0.030	-0.006	0.062	0.114***
	(0.000)	(0.129)	(0.331)	(0.968)	(0.671)	(0.000)
ΔCOVID Index	-0.133***	-0.057	-0.092**	-0.233	-0.480***	-0.008
	(0.001)	(0.165)	(0.027)	(0.232)	(0.010)	(0.846)

Panel B: The Pearson Correlation Between Sentiment Measures and Monthly Mood Proxies

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
Positive Months	0.037	-0.060**	0.012	0.040	0.053	0.011
	(0.235)	(0.055)	(0.698)	(0.802)	(0.715)	(0.721)
Negative Months	-0.222***	-0.182***	0.003	-0.069	-0.026	0.037
	(0.000)	(0.000)	(0.922)	(0.666)	(0.858)	(0.229)

Panel C: The Pearson Correlation Between Information Proxy and Six Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
%PositiveEANews	-0.015	-0.066**	0.104***	-0.056	0.343**	0.254***
	0.621	0.032	0.000	0.725	0.014	0.000

Table 4
Regressions of S&P 500 Index Returns on the Sentiment Indices

This table reports the regression estimates of Equation (2) from September 2020 to October 2024. The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]
GIFsentiment	0.199***	-0.235***	-1.068***
	(0.000)	(0.003)	(0.000)
EPU	0.001**	0.001	0.003**
	(0.011)	(0.126)	(0.021)
ADS	0.055	0.671***	1.828***
	(0.346)	(0.000)	(0.000)
Ret(t)		-0.074	-0.036
		(0.386)	(0.796)
Ret[t - 5, t - 1]	-0.031*	-0.067*	-0.127**
	(0.078)	(0.060)	(0.037)
Ret[t - 21, t - 6]	-0.007	-0.043*	-0.148***
	(0.532)	(0.053)	(0.000)
Log#EA	0.026	0.081	0.090
	(0.306)	(0.108)	(0.300)
Log#AbnMessages	-0.088	0.194	0.650*
	(0.219)	(0.318)	(0.070)
Observations	1,007	1,002	988
Adjusted R-squared	0.028	0.036	0.115

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]
GIFsentiment	0.141**	-0.071	-0.875***
	(0.020)	(0.554)	(0.000)
TEXTsentiment	0.161***	-0.017	0.510***
	(0.000)	(0.844)	(0.000)
SELFDEC	0.168**	0.069	0.540**
	(0.022)	(0.602)	(0.034)
BW	-0.403***	-0.427***	-1.534***
	(0.000)	(0.000)	(0.000)
ICS	-0.275***	0.038	0.351
	(0.000)	(0.732)	(0.127)
MEDIAsentiment	0.422***	-0.057	-0.348*
	(0.000)	(0.609)	(0.075)
EPU	0.001*	0.002*	0.004***
	(0.085)	(0.071)	(0.008)
ADS	0.059	0.810***	2.015***
	(0.354)	(0.000)	(0.000)
Ret(t)		-0.130	-0.210
		(0.154)	(0.172)
Ret[t - 5, t - 1]	-0.061***	-0.114***	-0.297***
	(0.001)	(0.005)	(0.000)
Ret[t - 21, t - 6]	-0.036***	-0.071***	-0.278***
	(0.001)	(0.004)	(0.000)
Log#EA	0.091***	0.127**	0.166*
	(0.002)	(0.027)	(0.079)
Log#AbnMessages	-0.168*	0.148	0.803*
	(0.050)	(0.505)	(0.082)
Observations	822	822	822
Adjusted R-squared	0.166	0.062	0.234

Table 5
Regressions of S&P 500 Index Returns on Positive and Negative GIF Sentiment

This table reports regression estimates from Equation (2), estimated over the period from September 2020 to October 2024, where GIFsentiment is replaced with its two components: PositiveGIFsentiment and NegativeGIFsentiment. PositiveGIFsentiment is constructed using only GIFs with a net positive sentiment score, while NegativeGIFsentiment is based on GIFs with a net negative sentiment score. The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]
PositiveGIFsentiment	0.177***	-0.103	-0.793***
	(0.000)	(0.228)	(0.000)
NegativeGIFsentiment	0.162***	-0.287***	-0.663***
	(0.000)	(0.000)	(0.000)
EPU	0.001*	0.002**	0.005***
	(0.076)	(0.023)	(0.000)
ADS	-0.038	0.837***	2.164***
	(0.551)	(0.000)	(0.000)
Ret(t)		-0.046	0.038
		(0.588)	(0.790)
Ret[t - 5, t - 1]	-0.031*	-0.071**	-0.136**
	(0.069)	(0.046)	(0.024)
Ret[t - 21, t - 6]	-0.007	-0.045**	-0.152***
	(0.533)	(0.040)	(0.000)
Log#EA	0.021	0.098*	0.116
	(0.398)	(0.050)	(0.181)
Log#AbnMessages	-0.055	0.348	0.935**
	(0.540)	(0.109)	(0.016)
Observations	1,006	1,001	987
Adjusted R-squared	0.050	0.045	0.125

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[$t + 1, t + 5$]	(3) Ret[$t + 1, t + 20$]
PositiveGIFsentiment	0.316***	-0.049	-0.661***
	(0.000)	(0.667)	(0.001)
NegativeGIFsentiment	0.483***	-0.028	0.496
	(0.000)	(0.870)	(0.112)
TEXTsentiment	0.070	-0.002	0.452***
	(0.106)	(0.986)	(0.001)
SELFDEC	0.166**	0.081	0.145
	(0.049)	(0.608)	(0.617)
BW	-0.559***	-0.421***	-1.713***
	(0.000)	(0.000)	(0.000)
ICS	-0.248***	0.041	0.404*
	(0.000)	(0.711)	(0.075)
MEDIAsentiment	0.419***	-0.074	-0.430**
	(0.000)	(0.509)	(0.028)
EPU	0.001	0.002*	0.004**
	(0.166)	(0.065)	(0.016)
ADS	0.036	0.826***	2.023***
	(0.565)	(0.000)	(0.000)
Ret(t)		-0.128	-0.234
		(0.173)	(0.138)
Ret[t - 5, t - 1]	-0.064***	-0.118***	-0.315***
	(0.000)	(0.004)	(0.000)
Ret[t - 21, t - 6]	-0.036***	-0.072***	-0.280***
	(0.001)	(0.004)	(0.000)
Log#EA	0.056**	0.129**	0.103
	(0.039)	(0.029)	(0.298)
Log#AbnMessages	-0.205*	0.347	1.296***
	(0.087)	(0.153)	(0.001)
Observations	821	821	821
Adjusted R-squared	0.212	0.062	0.238

Table 6
Intraday GIF Sentiment and Stock Returns

This table reports the regression estimates of Equation (2) from September 2020 to December 2023, using intraday return measures. The dependent variable is the Standard and Poor's ETF (SPY) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is measured at the 30-minute interval level per trading day. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

	(1)	(2)	(3)
VARIABLES	Ret(*t*)	Ret[*t* + 30m, *t* + 1d]	Ret[*t* + 30m, *t* + 2d]
GIFsentiment	0.054***	-0.032***	-0.076***
	(0.000)	(0.001)	(0.000)
EPU	0.000	-0.000	0.000
	(0.429)	(0.373)	(0.511)
ADS	-0.006	0.112***	0.245***
	(0.111)	(0.000)	(0.000)
Ret(*t*)		0.045	0.105
		(0.373)	(0.124)
Ret[*t* - 5, *t* - 1]	-0.014**	0.019	0.042
	(0.031)	(0.346)	(0.136)
Ret[*t* - 21, *t* - 6]	-0.005	0.005	-0.028*
	(0.115)	(0.628)	(0.068)
Log#EA	0.002	0.005	0.002
	(0.204)	(0.449)	(0.862)
Log#AbnMessages	-0.027***	0.019	-0.007
	(0.000)	(0.344)	(0.807)
Observations	10,493	10,481	10,468
Adjusted R-squared	0.0381	0.0049	0.0123

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[t + 30m, t + 1d]	(3) Ret[t + 30m, t + 2d]
GIFsentiment	0.016***	-0.017	-0.042**
	(0.000)	(0.164)	(0.015)
TEXTsentiment	0.023***	0.029***	0.041**
	(0.000)	(0.008)	(0.011)
SELFDEC	0.081***	-0.015	-0.031
	(0.000)	(0.368)	(0.191)
BW	-0.035***	-0.035***	-0.067***
	(0.000)	(0.001)	(0.000)
ICS	-0.032***	-0.010	-0.002
	(0.000)	(0.327)	(0.895)
MEDIAsentiment	-0.003	0.014*	0.010
	(0.154)	(0.092)	(0.416)
EPU	-0.000	-0.000	0.000
	(0.286)	(0.602)	(0.357)
ADS	-0.004	0.124***	0.267***
	(0.330)	(0.000)	(0.000)
Ret(t)		0.032	0.086
		(0.533)	(0.222)
Ret[t - 5, t - 1]	-0.034***	0.011	0.029
	(0.000)	(0.598)	(0.310)
Ret[t - 21, t - 6]	-0.012***	-0.000	-0.036**
	(0.000)	(0.971)	(0.018)
Log#EA	0.004**	0.005	0.001
	(0.013)	(0.491)	(0.880)
Log#AbnMessages	-0.054***	0.031	0.002
	(0.000)	(0.207)	(0.967)
Observations	10,493	10,481	10,468
Adjusted R-squared	0.0835	0.0007	0.0153

Table 7
GIF Sentiment and Limits to Arbitrage

This table reports the regression estimates of Equation (2) from September 2020 to October 2024. Panel A dependent variables are the value-weighted daily returns for the small (bottom quintile) and large (top quintile) cap portfolios, sorted based on market capitalization of the firm. Panel B dependent variables are the value-weighted daily returns for the top and bottom quintile portfolios, sorted based on idiosyncratic volatility using the Fama and French (1993) three factors and Cahart (1997) momentum factor. Panel C dependent variables are the value-weighted daily returns for the top and bottom quintile portfolios, sorted based on total return volatility. We multiply the returns by 100 so coefficients are interpreted as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A1: Small vs. Large Cap Index Returns; GIF Sentiment Alone

	Small Cap			Large Cap		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]
GIFsentiment	0.464***	-0.270	-2.225***	0.209***	-0.263***	-1.169***
	(0.000)	(0.195)	(0.000)	(0.000)	(0.001)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.038	0.017	0.0612	0.029	0.038	0.123
(Small-Large) p-values	0.000	0.657	0.011			

Panel A2: Small vs. Large Cap Index Returns; Six Sentiment Measures

	Small Cap			Large Cap		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]
GIFsentiment	0.245**	-0.226	-2.028***	0.142**	-0.091	-0.943***
	(0.030)	(0.436)	(0.001)	(0.020)	(0.455)	(0.000)
TEXTsentiment	0.134*	-0.591**	-2.565***	0.174***	-0.021	0.516***
	(0.053)	(0.028)	(0.000)	(0.000)	(0.819)	(0.000)
SELFDEC	0.568***	0.669	2.612***	0.203***	0.103	0.636**
	(0.003)	(0.176)	(0.002)	(0.007)	(0.459)	(0.015)
BW	-0.624***	-0.648**	-2.303***	-0.436***	-0.481***	-1.712***
	(0.000)	(0.029)	(0.000)	(0.000)	(0.000)	(0.000)
ICS	-0.482***	-0.227	0.428	-0.299***	0.023	0.319
	(0.001)	(0.533)	(0.455)	(0.000)	(0.844)	(0.171)
MEDIAsentiment	0.455***	0.251	0.938**	0.430***	-0.043	-0.354*
	(0.000)	(0.302)	(0.041)	(0.000)	(0.705)	(0.074)
Controls	YES	YES	YES	YES	YES	YES
Observations	822	822	822	822	822	822
Adjusted R-squared	0.113	0.042	0.202	0.178	0.066	0.255
(Small-Large) p-values	0.260	0.526	0.029			

Panel B1: High vs. Low Idiosyncratic Volatility of Returns; GIF Sentiment Alone

	High Idiosyncratic Volatility			Low Idiosyncratic Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]
GIFsentiment	0.526***	-0.729***	-3.883***	0.091***	-0.217***	-0.908***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.068	0.044	0.159	0.019	0.044	0.160
(High-Low) p-values	0.0000	0.010	0.0000			

Panel B2: High vs. Low Idiosyncratic Volatility of Returns; Six Sentiment Measures

	High Idiosyncratic Volatility			Low Idiosyncratic Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]
GIFsentiment	0.186*	-0.427	-4.030***	0.042	-0.168**	-0.956***
	(0.076)	(0.143)	(0.000)	(0.221)	(0.022)	(0.000)
TEXTsentiment	0.234***	-1.128***	-2.824***	0.078***	-0.050	0.095
	(0.002)	(0.000)	(0.000)	(0.000)	(0.312)	(0.198)
SELFDEC	1.025***	0.362	2.410***	0.117***	0.096	0.572***
	(0.000)	(0.384)	(0.004)	(0.005)	(0.225)	(0.000)
BW	-0.918***	-0.429*	-1.326**	-0.219***	-0.225***	-0.840***
	(0.000)	(0.070)	(0.011)	(0.000)	(0.000)	(0.000)
ICS	-0.789***	0.011	1.219**	-0.140***	0.038	0.215*
	(0.000)	(0.968)	(0.036)	(0.000)	(0.499)	(0.062)
MEDIAsentiment	0.565***	0.270	-0.074	0.209***	-0.018	-0.173
	(0.000)	(0.228)	(0.875)	(0.000)	(0.769)	(0.106)
Controls	YES	YES	YES	YES	YES	YES
Observations	822	822	822	822	822	822
Adjusted R-squared	0.238	0.093	0.295	0.161	0.071	0.288
(High-Low) p-values	0.013	0.220	0.0000			

Panel C1: High vs. Low Total Return Volatility; GIF Sentiment Alone

	High Total Return Volatility			Low Total Return Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]
GIFsentiment	0.547***	-0.547***	-3.289***	0.028***	-0.103***	-0.674***
	(0.000)	(0.004)	(0.000)	(0.007)	(0.001)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.059	0.036	0.121	0.039	0.076	0.161
(High-Low) p-values	0.0000	0.031	0.0000			

Panel C2: High vs. Low Total Return Volatility; Six Sentiment Measures

	High Total Return Volatility			Low Total Return Volatility		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]	Ret(t)	Ret[$t+1$, $t+5$]	Ret[$t+1$, $t+20$]
GIFsentiment	0.237**	-0.418	-4.159***	0.004	-0.009	-0.608***
	(0.037)	(0.152)	(0.000)	(0.792)	(0.855)	(0.000)
TEXTsentiment	0.151*	-1.262***	-3.510***	0.033***	-0.079***	0.038
	(0.074)	(0.000)	(0.000)	(0.003)	(0.008)	(0.546)
SELFDEC	0.948***	0.637*	3.412***	0.037*	-0.092*	-0.007
	(0.000)	(0.096)	(0.000)	(0.061)	(0.099)	(0.951)
BW	-0.812***	-0.245	-0.300	-0.068***	-0.062*	-0.406***
	(0.000)	(0.276)	(0.523)	(0.000)	(0.082)	(0.000)
ICS	-0.714***	0.042	1.454***	-0.034***	0.098***	0.414***
	(0.000)	(0.868)	(0.007)	(0.002)	(0.006)	(0.000)
MEDIAsentiment	0.643***	0.342	0.096	0.060***	-0.003	-0.031
	(0.000)	(0.139)	(0.838)	(0.000)	(0.944)	(0.711)
Controls	YES	YES	YES	YES	YES	YES
Observations	822	822	822	822	822	822
Adjusted R-squared	0.215	0.102	0.313	0.119	0.132	0.278
(High-Low) p-values	0.025	0.175	0.0000			

Table 8
Regressions of Stock Market Volatility on the Sentiment Proxies

This table reports the regression estimates of Equation (3) from September 2020 to October 2024. The dependent variable, Volatility% is the standard deviation of daily S&P 500 Index return during day t and t + 5. The main independent variable, |GIFsentiment| is the absolute value of daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Randomization p-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

VARIABLES	(1) Volatility[t, t + 5](%)	(2) Volatility [t, t + 5](%)	(3) Volatility [t, t + 20](%)	(4) Volatility [t, t + 20](%)
|GIFsentiment|	0.047**	0.070**	0.024	0.038*
	(0.029)	(0.019)	(0.134)	(0.070)
|TEXTsentiment|		-0.068***		-0.042***
		(0.000)		(0.000)
|SELFDEC|		-0.089***		-0.053**
		(0.010)		(0.034)
|BW|		-0.132***		-0.060**
		(0.000)		(0.019)
|ICS|		-0.014***		-0.013***
		(0.000)		(0.000)
|MEDIAsentiment|		0.021		-0.006
		(0.380)		(0.745)
EPU	0.000**	0.000	0.000**	0.000
	(0.027)	(0.101)	(0.045)	(0.714)
ADS	0.012	-0.019	-0.015	-0.034
	(0.618)	(0.451)	(0.442)	(0.111)
Ret[t - 5, t - 1]	-0.062***	-0.066***	-0.034***	-0.036***
	(0.000)	(0.000)	(0.000)	(0.000)
Ret[t - 21, t - 6]	-0.025***	-0.029***	-0.014***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)
Volatility%[t - 5, t - 1]	0.235***	0.195***	0.257***	0.248***
	(0.000)	(0.000)	(0.000)	(0.000)
Log#EA	0.048***	0.051***	0.016**	0.018**
	(0.000)	(0.000)	(0.014)	(0.021)
Log#AbnMessages	0.035	0.037	0.008	0.001
	(0.219)	(0.242)	(0.792)	(0.980)
Observations	1,007	822	1,007	822
Adjusted R-Squared	0.412	0.427	0.438	0.444

Table 9
GIF Sentiment, GIF Disagreement, and Trading Volume

This table reports the regression estimates of Equation (4), examining the relationship between sentiment and total trading volume. The analysis uses intraday data from September 2020 to December 2023 to construct return and sentiment measures at the 30-minute interval level. The dependent variable, LogTotalVol, is defined as the natural logarithm of one plus the total SPY trading volume accumulated within a given 30-minute interval t, as well as over forward-looking windows from t + 30 minutes to t + 1 day and from t + 30 minutes to t + 2 days. In Panel A, the main independent variable, |GIFsentiment|, is the absolute value of the appearance-weighted average sentiment of GIFs posted on Stocktwits during 30-minute interval t. In Panel B, we use GIFDisagreement, an intraday dispersion-based sentiment measure at t, constructed as defined in Equation (5). GIFsentiment, TEXTsentiment, SELFDEC, BW, ICS, and MEDIAsentiment are standardized to have zero mean and unit variance. Randomization p-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment and Total Trading Volume

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LogTotalVol(t)	LogTotalVol [t + 30m, t + 1d]	LogTotalVol(t) [t + 30m, t + 2d]	LogTotalVol(t)	LogTotalVol [t + 30m, t + 1d]	LogTotalVol(t) [t + 30m, t + 2d]
|GIFsentiment|	0.162***	0.036***	0.034***	0.152***	0.054***	0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|TEXTsentiment|				-0.078**	0.033***	0.032***
				(0.031)	(0.000)	(0.000)
|SELFDEC|				-0.016	-0.089***	-0.098***
				(0.573)	(0.000)	(0.000)
|BW|				-0.143***	-0.037***	-0.047***
				(0.000)	(0.001)	(0.000)
|ICS|				-0.177***	-0.064***	-0.070***
				(0.000)	(0.000)	(0.000)
|MEDIAsentiment|				-0.031	-0.011*	0.002
				(0.158)	(0.068)	(0.762)
Controls	YES	YES	YES	YES	YES	YES
Observations	10,493	10,493	10,493	10,493	10,493	10,493
Adjusted R-squared	0.080	0.268	0.304	0.153	0.400	0.432

Panel B: GIF Disagreement and Total Trading Volume

VARIABLES	(1) LogTotalVol(t)	(2) LogTotalVol [t + 30m, t + 1d]	(3) LogTotalVol(t) [t + 30m, t + 2d]	(4) LogTotalVol(t)	(5) LogTotalVol [t + 30m, t + 1d]	(6) LogTotalVol(t) [t + 30m, t + 2d]
GIFDisagreement	0.246***	0.133***	0.125***	0.213***	0.102***	0.094***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
|TEXTsentiment|				0.069***	0.033***	0.033***
				(0.004)	(0.000)	(0.000)
|SELFDEC|				-0.069***	-0.085***	-0.086***
				(0.004)	(0.000)	(0.000)
|BW|				-0.091***	-0.068***	-0.075***
				(0.002)	(0.000)	(0.000)
|ICS|				-0.098***	-0.091***	-0.095***
				(0.000)	(0.000)	(0.000)
|MEDIAsentiment|				-0.072***	-0.031***	-0.027***
				(0.000)	(0.000)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	10,493	10,493	10,493	10,493	10,493	10,493
Adjusted R-squared	0.105	0.331	0.366	0.109	0.352	0.388

Table 10
Regression of Equity and Bond Fund Flows on the Sentiment Proxies

This table reports the regression estimates of Equation (6) from September 2020 to May 2023. In Panel A, the dependent variable, EFF is the daily net equity fund flow scaled by the fund's assets under management. In Panel B, BFF is the daily net bond fund flow scaled by the fund's assets under management. For both Panel A and B, we regress EFF and BFF on day-of-week and month-of-year dummies to remove seasonality and use the residuals as the dependent variables. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: Equity Fund Flow

	(1)	(2)	(3)	(5)
VARIABLES	EFF(t)	EFF[t +1, t + 5]	EFF(t)	EFF[t + 1, t + 5]
GIFsentiment	0.037**	0.002***	0.040**	0.002*
	(0.020)	(0.010)	(0.050)	(0.066)
TEXTsentiment			-0.023	-0.001
			(0.301)	(0.192)
SELFDEC			0.028	0.001
			(0.403)	(0.379)
BW			-0.007	0.001
			(0.788)	(0.729)
ICS			0.022	-0.001
			(0.515)	(0.597)
MEDIAsentiment			0.011	-0.001
			(0.540)	(0.467)
Controls	YES	YES	YES	YES
Observations	650	649	648	646
Adjusted R-squared	0.014	0.027	0.019	0.059

Panel B1: Bond Fund Flow

	(1)	(2)	(3)	(5)
VARIABLES	BFF(t)	BFF[t + 1, t + 5]	BFF(t)	BFF[t + 1, t + 5]
GIF sentiment	-0.037**	-0.006***	-0.037	-0.004***
	(0.020)	(0.000)	(0.251)	(0.010)
Text sentiment			-0.012	-0.001
			(0.458)	(0.144)
SELFDEC			0.039	0.004**
			(0.264)	(0.021)
BW sentiment			-0.031	-0.009***
			(0.192)	(0.000)
ICS			-0.063***	0.012***
			(0.009)	(0.000)
Media sentiment			0.024	-0.001
			(0.240)	(0.409)
Controls	YES	YES	YES	YES
Observations	650	649	648	646
Adjusted R-squared	0.102	0.027	0.114	0.485

Table A1
GIFs with Top 25 Highest and Top 25 Lowest Valence

This table reports the GIFs with the top 25 highest and lowest sentiment throughout our sample period. Sentiment for each GIF is calculated as the difference between the total number of bullish declarations and bearish declarations, divided by the total number of appearances for each GIF during our sample period. All Giphy.com GIFs share a uniform URL structure: https://media2.giphy.com/media/{gif.id}/giphy.gif. To view the animated GIFs, substitute {gif.id} with the corresponding value in the Giphy_ID column.

GIFs with lowest valence		GIFs with highest valence	
Giphy_ID	Valence	Giphy_ID	Valence
l41YdlqVlryxP91Sw	-0.957	xTiTnkt1IjaaTWoPny	0.996
WRbRNyAjA0mIw	-0.884	2cpPfXUit2JSU	0.995
kfd19XS70QrTQmsw7k	-0.866	f9AxU1ieQdqfHbbf13	0.995
UfX4XeBMXWmNoGvBVK	-0.816	ibhRKzDTJ7O12	0.991
IQ9KefLJHfJPq	-0.779	XZVYAstOMLUDndgFPS	0.972
xA5oN4RDaCneQfcC8x	-0.761	YpwSw00aOaoIhPVSAF	0.971
9gGi02YPpLo2ueSxvh	-0.744	PnahEQ7Ify1JvhQrag	0.968
NUZ5OqHdbknHa	-0.744	mCsoBwnIyB5PSYwsAo	0.943
utMwbVuNZSSlvej2En	-0.734	9z8Jpk8Sl9QRrWqXlR	0.940
l0K4puBUN4w6G4ksE	-0.727	3ohjUQnfcfYR0QA3Yc	0.940
JpN6nbJqz5l3mbMnod	-0.722	1AeRujyfNSXi35GDU8	0.938
3LcOi1fXmCzNaYyemC	-0.691	qrfjUqL8RPqmNB5LQM	0.936
m6tNZJt9cG3ss	-0.676	ULoie47jnvxwtkx90t	0.935
dvZSDOywoCM4Sro65Q	-0.674	QMyF0t2nkwNNt2sJp2	0.934
ERIB4ws3cw17uWN4mF	-0.673	dYyM2kbL89gYVS73IM	0.933
9l84gf0TK6B7C3UCZp	-0.671	3o6wNKjI7XkipBHUjK	0.928
LkuPxRS0F6gmc	-0.661	9rjzS2QYAk1paKD7uk	0.926
9detkWt4jBdhVm0UCk	-0.658	HGvjR72DXRHWw	0.925
y31rRE5h3wyPXey8vx	-0.654	HxtPXNp0ahLyM	0.925
C5ZIna5oroan9cdHz9	-0.652	VF6zQwFDlpE12FzBUB	0.922
VjzHEo2kXOxtJOJRCS	-0.649	eu5jaVImGyKnsohsGy	0.920
JmUrefXyfqajgUNd0p	-0.642	bEIQpE3d1sENO	0.919
11Y9TiZzmEBe25QRSw	-0.640	6xE1FNcorRInS	0.915
LcS32DLbuturC	-0.632	l4Ep9KQRRXtyjkIWQ	0.914
w4NAKAenurl8k	-0.623	3xz2BzSNxkwPqF8Wdy	0.914

Table A2 Variable Definitions

Variable	Definition	Source
ADS	U.S. macroeconomic activity index.	Aruoba et al. (2009)
Bond Fund Flow (BFF)	Daily aggregated mutual fund flow that specialize in US bonds.	EPFR
BW	Baker-Wugler monthly sentiment index.	https://pages.stern.nyu.edu/~jwurgler/
Covid_Index	Daily index based on COVID-19's lockdown restrictions, including school closures, workplace closures, cancellations of public events, restrictions on gathering sizes, closures of public transport, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel. The index ranges from 0 to 21.	University of Oxford's COVID-19 government response tracker
DCC	Daily average cloud cover using hourly values from 6am to 12pm across the country's weather stations. We deseasonalize the average daily cloud cover by subtracting each week's mean cloud cover from each daily mean following Hirshleifer and Shumway (2003).	National Oceanic and Atmospheric Administration
Equity Fund Flow (EFF)	Daily aggregated mutual fund flow that specialize in US equity.	EPFR
EPU	News-based measure of U.S. economic policy uncertainty.	Baker et al. (2016)
GIFsentiment	Daily average sentiment of GIFs in all postings with cashtags (including both single and multiple cashtags), standardized to have a zero mean and unit variance.	Stocktwits
ICS	Monthly consumer confidence index.	University of Michigan's Surveys of Consumers
Log#AbnMessages	The deviation from the median number of messages posted over the prior 10 trading days.	Stocktwits
Log#EA	Daily natural logarithm of one plus the number of earnings announcements.	COMPUSTAT
MEDIAsentiment	Daily measure of traditional news media sentiment.	RavenPack
SELFDEC	Daily average sentiment of users' self-declarations in all non-GIF postings, standardized to have a zero mean and unit variance.	Stocktwits
SPX (%)	Daily return of S&P 500 Index.	CRSP
SPY (%)	30-min interval intraday return of SPDR S&P 500 ETF.	TAQ
Textsentiment	Daily average sentiment of text in all postings, standardized to have a zero mean and unit variance.	Stocktwits

Table A3 User Characteristics and The Use of GIFs and Self-Declarations

Panel A: User Characteristics and The Use of GIFs

DEP.VAR=	GIF_Dummy_i	$Log(\#GIF)_i$
$\mathbb{1}Declared_Novice_i$	0.026***	0.023***
	(0.004)	(0.008)
$\mathbb{1}Declared_Intermediate_i$	-0.001	-0.028***
	(0.003)	(0.006)
$\mathbb{1}Declared_Professional_i$	-0.039***	-0.101***
	(0.004)	(0.010)
$Activedays_i$	0.163***	0.450***
	(0.000)	(0.001)
$Log(\#followers)_i$	-0.026***	-0.038***
	(0.001)	(0.001)
$\mathbb{1}User_bio_i$	0.059***	0.159***
	(0.002)	(0.005)
$Mean(Text\ sentiment)_i$	0.001	0.043***
	(0.002)	(0.006)
$Mean(\#Word)_i$	-0.002***	-0.003***
	(0.000)	(0.000)
$Mean(\#Number)_i$	-0.007***	-0.013***
	(0.000)	(0.001)
$Mean(\#Emoji)_i$	0.015***	0.047***
	(0.001)	(0.001)
Observations	474,488	474,488
Adjusted R-squared	0.237	0.325

Panel B: User Characteristics and The Use of Self-Declarations

DEP.VAR=	$SELFDEC_Dummy_i$	$Log(\#SELFDEC)_i$
$\mathbb{1}Declared_Novice_i$	-0.008*	-0.081***
	(0.005)	(0.011)
$\mathbb{1}Declared_Intermediate_i$	0.020***	0.014*
	(0.003)	(0.008)
$\mathbb{1}Declared_Professional_i$	0.050***	0.128***
	(0.006)	(0.014)
$Activedays_i$	-0.032***	0.275***
	(0.001)	(0.002)
$Log(\#followers)_i$	-0.000	0.013***
	(0.001)	(0.002)
$\mathbb{1}User_bio_i$	-0.036***	-0.120***
	(0.003)	(0.007)
$Mean(Text\ sentiment)_i$	0.063***	0.090***
	(0.003)	(0.008)
$Mean(\#Word)_i$	0.001***	-0.000
	(0.000)	(0.000)
$Mean(\#Number)_i$	0.006***	0.012***
	(0.000)	(0.001)
$Mean(\#Emoji)_i$	-0.003***	-0.004**
	(0.001)	(0.002)
Observations	474,488	474,488
Adjusted R-squared	0.011	0.090

Panel C: Correlation Between GIF Sentiment from Self-declarations and GPT-Coded Sentiment

VARIABLES	(1) $ST\text{-}GIFsentiment_{continuous}$	(2) $ST\text{-}GIFsentiment_{binary}$
$Gpt4v\text{-}GIFsentiment_{continuous}$	0.485***	
	<0.0001	
$Gpt4v\text{-}GIFsentiment_{binary}$		0.814***
		<0.0001

Table A4
Robustness to Winsorize Returns at the top and bottom 1%, 5%, and 10% levels.

This table reports the regression estimates of Equation (2). The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We Winsorize returns at the top and bottom 1%, 5%, and 10% levels. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Winsorize at top and bottom 1 percentile			Winsorize at top and bottom 5 percentile			Winsorize at top and bottom 10 percentile		
VARIABLES	Ret(t)	Ret[$t+1, t+5$]	Ret[$t+1, t+20$]	Ret(t)	Ret[$t+1, t+5$]	Ret[$t+1, t+20$]	Ret(t)	Ret[$t+1, t+5$]	Ret[$t+1, t+20$]
GIFsentiment	0.197***	-0.214***	-0.975***	0.175***	-0.215***	-0.863***	0.155***	-0.188***	-0.716***
	(0.000)	(0.005)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
EPU	0.001**	0.001	0.004**	0.001**	0.001	0.004***	0.001**	0.001	0.004***
	(0.011)	(0.148)	(0.011)	(0.016)	(0.206)	(0.001)	(0.023)	(0.306)	(0.001)
ADS	0.064	0.707***	1.918***	0.057	0.638***	1.763***	0.045	0.537***	1.471***
	(0.250)	(0.000)	(0.000)	(0.269)	(0.000)	(0.000)	(0.322)	(0.000)	(0.000)
Ret(t)		-0.077	-0.108		-0.084	-0.132		-0.094	-0.129
		(0.356)	(0.410)		(0.277)	(0.279)		(0.216)	(0.287)
Ret[$t-5, t-1$]	-0.032*	-0.081**	-0.183***	-0.034**	-0.069**	-0.178***	-0.037**	-0.068**	-0.155***
	(0.070)	(0.020)	(0.002)	(0.034)	(0.034)	(0.002)	(0.020)	(0.036)	(0.007)
Ret[$t-21, t-6$]	-0.011	-0.057***	-0.157***	-0.011	-0.056***	-0.111***	-0.010	-0.050**	-0.061*
	(0.275)	(0.010)	(0.000)	(0.238)	(0.006)	(0.002)	(0.283)	(0.011)	(0.083)
Log#EA	0.022	0.075	0.082	0.019	0.082*	0.106	0.015	0.070*	0.069
	(0.353)	(0.121)	(0.321)	(0.343)	(0.055)	(0.151)	(0.396)	(0.062)	(0.285)
Log#AbnMessages	-0.087	0.195	0.608*	-0.075	0.182	0.523	-0.064	0.168	0.450
	(0.210)	(0.317)	(0.089)	(0.239)	(0.306)	(0.109)	(0.252)	(0.292)	(0.128)
Observations	1,007	1,002	988	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.030	0.042	0.127	0.031	0.046	0.130	0.031	0.042	0.116

Panel B: Six Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Winsorize at top and bottom 1 percentile			Winsorize at top and bottom 5 percentile			Winsorize at top and bottom 10 percentile		
VARIABLES	Ret(*t*)	Ret[*t* + 1, *t* + 5]	Ret[*t* + 1, *t* + 20]	Ret(*t*)	Ret[*t* + 1, *t* + 5]	Ret[*t* + 1, *t* + 20]	Ret(*t*)	Ret[*t* + 1, *t* + 5]	Ret[*t* + 1, *t* + 20]
GIFsentiment	0.133**	-0.083	-0.889***	0.091*	-0.167	-0.935***	0.084*	-0.168*	-0.876***
	(0.025)	(0.471)	(0.000)	(0.090)	(0.105)	(0.000)	(0.100)	(0.084)	(0.000)
TEXTsentiment	0.165***	0.018	0.579***	0.153***	0.042	0.483***	0.144***	0.044	0.444***
	(0.000)	(0.834)	(0.000)	(0.000)	(0.573)	(0.000)	(0.000)	(0.535)	(0.000)
SELFDEC	0.183**	0.162	0.850***	0.201***	0.258**	1.043***	0.195***	0.251**	0.975***
	(0.014)	(0.209)	(0.000)	(0.004)	(0.028)	(0.000)	(0.003)	(0.025)	(0.000)
BW	-0.410***	-0.491***	-1.660***	-0.361***	-0.451***	-1.450***	-0.337***	-0.421***	-1.317***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICS	-0.276***	-0.009	0.195	-0.240***	-0.019	0.131	-0.221***	-0.001	0.194
	(0.000)	(0.935)	(0.354)	(0.000)	(0.832)	(0.437)	(0.000)	(0.992)	(0.216)
MEDIAsentiment	0.416***	-0.036	-0.380**	0.352***	-0.015	-0.338**	0.330***	0.004	-0.313**
	(0.000)	(0.737)	(0.036)	(0.000)	(0.872)	(0.034)	(0.000)	(0.968)	(0.040)
EPU	0.001*	0.002	0.004***	0.001	0.001	0.004***	0.000	0.001	0.004***
	(0.088)	(0.101)	(0.007)	(0.139)	(0.179)	(0.002)	(0.167)	(0.243)	(0.001)
ADS	0.075	0.853***	2.157***	0.053	0.723***	1.899***	0.040	0.654***	1.751***
	(0.217)	(0.000)	(0.000)	(0.327)	(0.000)	(0.000)	(0.436)	(0.000)	(0.000)
Ret(*t*)	.	-0.159*	-0.346**	.	-0.192**	-0.416***	.	-0.204**	-0.415***
	(.)	(0.075)	(0.014)	(.)	(0.023)	(0.001)	(.)	(0.015)	(0.001)
Ret[*t* - 5, *t* - 1]	-0.068***	-0.143***	-0.408***	-0.074***	-0.145***	-0.434***	-0.075***	-0.143***	-0.423***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ret[*t* - 21, *t* - 6]	-0.045***	-0.098***	-0.324***	-0.048***	-0.108***	-0.306***	-0.048***	-0.107***	-0.284***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log#EA	0.088***	0.135**	0.194**	0.076***	0.139***	0.213***	0.071***	0.128***	0.182**
	(0.001)	(0.015)	(0.027)	(0.001)	(0.004)	(0.006)	(0.001)	(0.005)	(0.015)
Log#AbnMessages	-0.163**	0.143	0.770	-0.129*	0.143	0.659	-0.116	0.140	0.640
	(0.048)	(0.527)	(0.114)	(0.087)	(0.498)	(0.154)	(0.109)	(0.495)	(0.157)
Observations	822	822	822	822	822	822	822	822	822
Adjusted R-squared	0.181	0.0745	0.275	0.183	0.0831	0.289	0.178	0.084	0.279

Table A5
Robustness to GIF Appearance Frequency Thresholds

This table reports the regression estimates of Equation (2). The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits, using only GIFs whose cumulative appearances exceed the 50th or 75th percentile among all GIFs as of day *t*. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

	(1)	(2)	(3)	(4)	(5)	(6)
	Keep only GIFs whose cumulative appearances exceed the 50th percentile			Keep only GIFs whose cumulative appearances exceed the 75th percentile		
VARIABLES	Ret(*t*)	Ret[*t* + 1, t + 5]	Ret[*t* + 1, *t* + 20]	Ret(*t*)	Ret[*t* + 1, *t* + 5]	Ret[*t* + 1, *t* + 20]
GIFsentiment	0.183***	-0.171**	-1.067***	0.188***	-0.120	-0.907***
	(0.000)	(0.040)	(0.000)	(0.000)	(0.126)	(0.000)
EPU	0.001***	0.001	0.002	0.001***	0.001	0.002
	(0.005)	(0.152)	(0.212)	(0.003)	(0.114)	(0.147)
ADS	0.122**	0.595***	1.479***	0.156***	0.574***	1.326***
	(0.035)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
Ret(*t*)		-0.087	-0.062		-0.092	-0.076
		(0.308)	(0.660)		(0.280)	(0.592)
Ret[*t* - 5, *t* - 1]	-0.028	-0.072**	-0.140**	-0.029*	-0.073**	-0.140**
	(0.112)	(0.043)	(0.023)	(0.096)	(0.041)	(0.023)
Ret[*t* - 21, *t* - 6]	-0.004	-0.046**	-0.160***	-0.005	-0.045**	-0.158***
	(0.676)	(0.041)	(0.000)	(0.644)	(0.043)	(0.000)
Log#EA	0.019	0.091*	0.126	0.018	0.094*	0.137
	(0.455)	(0.073)	(0.147)	(0.471)	(0.067)	(0.119)
Log#AbnMessages	-0.082	0.174	0.612	-0.078	0.163	0.569
	(0.248)	(0.391)	(0.110)	(0.269)	(0.432)	(0.154)
Observations	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.021	0.032	0.110	0.023	0.030	0.098

Panel B: Six Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)
	Keep only GIFs whose cumulative appearances exceed the 50th percentile			Keep only GIFs whose cumulative appearances exceed the 75th percentile		
VARIABLES	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]
GIFsentiment	0.130**	0.014	-0.792***	0.138***	-0.026	-0.957***
	(0.014)	(0.897)	(0.000)	(0.007)	(0.805)	(0.000)
TEXTsentiment	0.153***	-0.039	0.553***	0.146***	-0.025	0.638***
	(0.000)	(0.666)	(0.000)	(0.001)	(0.784)	(0.000)
SELFDEC	0.209***	0.016	0.277	0.217***	0.030	0.267
	(0.001)	(0.896)	(0.226)	(0.000)	(0.797)	(0.229)
BW	-0.401***	-0.445***	-1.551***	-0.390***	-0.439***	-1.606***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICS	-0.261***	0.054	0.263	-0.245***	0.040	0.125
	(0.000)	(0.639)	(0.268)	(0.000)	(0.737)	(0.611)
MEDIAsentiment	0.425***	-0.042	-0.361*	0.425***	-0.050	-0.390**
	(0.000)	(0.705)	(0.066)	(0.000)	(0.652)	(0.046)
EPU	0.001*	0.002*	0.004**	0.001*	0.002*	0.003**
	(0.078)	(0.053)	(0.010)	(0.075)	(0.062)	(0.020)
ADS	0.063	0.818***	1.988***	0.065	0.812***	1.963***
	(0.316)	(0.000)	(0.000)	(0.306)	(0.000)	(0.000)
Ret(t)		-0.135	-0.211		-0.132	-0.198
		(0.140)	(0.174)		(0.147)	(0.201)
Ret[t - 5, t - 1]	-0.061***	-0.114***	-0.299***	-0.061***	-0.114***	-0.297***
	(0.001)	(0.005)	(0.000)	(0.001)	(0.005)	(0.000)
Ret[t - 21, t - 6]	-0.036***	-0.071***	-0.277***	-0.036***	-0.071***	-0.278***
	(0.001)	(0.004)	(0.000)	(0.001)	(0.004)	(0.000)
Log#EA	0.088***	0.128**	0.182*	0.087***	0.128**	0.187**
	(0.002)	(0.027)	(0.054)	(0.003)	(0.027)	(0.046)
Log#AbnMessages	-0.176**	0.129	0.846*	-0.181**	0.141	0.912*
	(0.043)	(0.566)	(0.080)	(0.038)	(0.531)	(0.061)
Observations	822	822	822	822	822	822
Adjusted R-squared	0.166	0.061	0.234	0.166	0.0613	0.241

Table A6
Robustness to Post Estimation Check

This table reports the regression estimates of Equation (2). We exclude observations with high influence as identified by the DFBETA test, where influence is defined as having an absolute DFBETA greater than $2/\sqrt{n}$, with n denoting the sample size. DFBETA quantifies the impact of each observation on the estimated regression coefficient for GIFsentiment by comparing the coefficient with and without that observation. The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

VARIABLES	(1) Ret(*t*) Exclude 34 days with large DFBETA values	(2) Ret[*t* + 1, *t* + 5] Exclude 33 days with large DFBETA values	(3) Ret[*t* + 1, *t* + 20] Exclude 25 days with large DFBETA values
GIFsentiment	0.182***	-0.258***	-1.029***
	(0.000)	(0.000)	(0.000)
EPU	0.001	0.001	0.004***
	(0.145)	(0.193)	(0.002)
ADS	0.029	0.712***	1.837***
	(0.587)	(0.000)	(0.000)
Ret(*t*)		-0.024	-0.003
		(0.769)	(0.985)
Ret[*t* - 5, *t* - 1]	-0.027	-0.067**	-0.100*
	(0.111)	(0.042)	(0.095)
Ret[*t* - 21, *t* - 6]	-0.009	-0.047**	-0.190***
	(0.330)	(0.027)	(0.000)
Log#EA	0.032	0.034	0.095
	(0.182)	(0.480)	(0.256)
Log#AbnMessages	-0.075	0.429**	1.021***
	(0.225)	(0.032)	(0.006)
Observations	973	969	963
Adjusted R-squared	0.022	0.042	0.127

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(*t*) Exclude 52 days with large DFBETA values	(2) Ret[*t* + 1, *t* + 5] Exclude 49 days with large DFBETA values	(3) Ret[*t* + 1, *t* + 20] Exclude 54 days with large DFBETA values
GIFsentiment	0.124***	-0.194**	-1.089***
	(0.007)	(0.037)	(0.000)
TEXTsentiment	0.172***	-0.003	0.497***
	(0.000)	(0.974)	(0.000)
SELFDEC	0.167***	0.102	0.715***
	(0.007)	(0.409)	(0.003)
BW	-0.430***	-0.467***	-1.780***
	(0.000)	(0.000)	(0.000)
ICS	-0.296***	0.049	0.434**
	(0.000)	(0.652)	(0.037)
MEDIAsentiment	0.484***	-0.028	-0.379**
	(0.000)	(0.781)	(0.041)
EPU	0.000	0.002	0.003**
	(0.402)	(0.147)	(0.014)
ADS	0.104*	0.835***	2.243***
	(0.073)	(0.000)	(0.000)
Ret(*t*)		-0.149*	-0.097
		(0.069)	(0.490)
Ret[*t* - 5, *t* - 1]	-0.061***	-0.100***	-0.279***
	(0.000)	(0.009)	(0.000)
Ret[*t* - 21, *t* - 6]	-0.040***	-0.077***	-0.360***
	(0.000)	(0.001)	(0.000)
Log#EA	0.081***	0.103**	0.028
	(0.001)	(0.047)	(0.753)
Log#AbnMessages	-0.234***	0.091	0.706*
	(0.002)	(0.636)	(0.078)
Observations	770	773	768
Adjusted R-squared	0.230	0.078	0.316

Table A7
Robustness to Excluding the Initial Adoption Period

This table reports the regression estimates of Equation (2). We exclude observations from the initial adoption period of the GIF-sending function on Stocktwits.com, spanning September 1, 2020 to December 31, 2020. The dependent variable is the Standard and Poor's 500 Index (SPX) return at alternative windows. We multiply returns by 100 to interpret coefficients as percentage points. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. Sentiment measures are standardized to have zero mean and unit variance. Randomization *p*-values are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

	(1)	(2)	(3)
VARIABLES	Ret(t)	Ret[t + 1, t + 5]	Ret[t + 1, t + 20]
GIFsentiment	0.261***	-0.295***	-1.195***
	(0.000)	(0.000)	(0.000)
EPU	0.000	0.001	0.004**
	(0.262)	(0.548)	(0.016)
ADS	-0.007	0.788***	2.036***
	(0.915)	(0.000)	(0.000)
Ret(t)		-0.062	0.038
		(0.488)	(0.800)
Ret[t - 5, t - 1]	-0.035*	-0.042	-0.082
	(0.058)	(0.261)	(0.207)
Ret[t - 21, t - 6]	-0.006	-0.034	-0.169***
	(0.599)	(0.145)	(0.000)
Log#EA	0.033	0.070	0.021
	(0.221)	(0.196)	(0.822)
Log#AbnMessages	-0.094	0.123	0.707*
	(0.202)	(0.513)	(0.061)
Observations	926	921	907
Adjusted R-squared	0.037	0.032	0.103

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]
GIFsentiment	0.212**	-0.376**	-2.281***
	(0.018)	(0.021)	(0.000)
TEXTsentiment	0.124***	-0.154	0.336*
	(0.009)	(0.150)	(0.057)
SELFDEC	0.099	0.318**	1.775***
	(0.312)	(0.049)	(0.000)
BW	-0.419***	-0.462***	-1.711***
	(0.000)	(0.000)	(0.000)
ICS	-0.287***	0.022	0.266
	(0.000)	(0.849)	(0.250)
MEDIAsentiment	0.500***	-0.022	-0.343
	(0.000)	(0.855)	(0.114)
EPU	0.001	0.001	0.006***
	(0.177)	(0.153)	(0.000)
ADS	0.057	0.988***	2.403***
	(0.396)	(0.000)	(0.000)
Ret(t)		-0.115	-0.114
		(0.241)	(0.490)
Ret[t - 5, t - 1]	-0.059***	-0.085**	-0.254***
	(0.001)	(0.042)	(0.000)
Ret[t - 21, t - 6]	-0.030***	-0.066**	-0.334***
	(0.007)	(0.012)	(0.000)
Log#EA	0.080***	0.103*	0.061
	(0.007)	(0.091)	(0.538)
Log#AbnMessages	-0.184**	0.063	0.931**
	(0.032)	(0.749)	(0.029)
Observations	741	741	741
Adjusted R-squared	0.192	0.062	0.255

Table A8
Robustness to Using Moving Block Bootstrap

This table presents robustness tests of the regression estimates from Equation (2), where standard errors (reported in parentheses) are computed using the moving block bootstrap. We report results based on a small block size (n=10) and a large block size (n=30). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A2.

Panel A: GIF Sentiment Alone

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]	(4) Ret(t)	(5) Ret[t + 1, t + 5]	(6) Ret[t + 1, t + 20]
	Small Block Size (n=10)			Large Block Size (n=30)		
GIFsentiment	0.215***	-0.308**	-1.765***	0.246***	-0.390***	-0.989**
	(0.064)	(0.149)	(0.328)	(0.079)	(0.151)	(0.431)
EPU	0.000	0.001	0.001	0.002***	-0.002	0.002
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
ADS	0.026	0.725**	2.650***	0.157	1.359***	3.012***
	(0.105)	(0.299)	(0.533)	(0.107)	(0.278)	(0.790)
Ret(t)		-0.025	-0.089		-0.169	-0.060
		(0.151)	(0.189)		(0.132)	(0.228)
Ret[t - 5, t - 1]	-0.038	0.007	-0.172	-0.036	-0.080	-0.188
	(0.027)	(0.063)	(0.134)	(0.027)	(0.073)	(0.127)
Ret[t - 21, t - 6]	-0.009	-0.077	-0.298***	-0.009	-0.050	-0.095
	(0.018)	(0.052)	(0.108)	(0.014)	(0.046)	(0.120)
Log#EA	0.035	0.153	0.207	0.073	0.052	-0.022
	(0.042)	(0.108)	(0.221)	(0.045)	(0.122)	(0.235)
Log#AbnMessages	-0.179	0.856**	0.742	-0.116	-0.103	0.508
	(0.145)	(0.379)	(0.883)	(0.146)	(0.364)	(0.805)
Observations	1,007	1,002	988	1,007	1,002	988
Adjusted R-squared	0.031	0.068	0.275	0.044	0.081	0.194

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[t + 1, t + 5]	(3) Ret[t + 1, t + 20]	(4) Ret(t)	(5) Ret[t + 1, t + 5]	(6) Ret[t + 1, t + 20]
	Small Block Size (n=10)			Large Block Size (n=30)		
GIFsentiment	0.187*	-0.037	-1.046**	0.191*	-0.120	-1.135*
	(0.106)	(0.286)	(0.457)	(0.107)	(0.262)	(0.600)
TEXTsentiment	0.120*	0.003	0.092	0.205**	-0.203	0.501
	(0.071)	(0.186)	(0.390)	(0.084)	(0.178)	(0.377)
SELFDEC	-0.026	-0.128	0.467	0.259*	0.336	1.417*
	(0.122)	(0.350)	(0.567)	(0.142)	(0.331)	(0.773)
BW	-0.401***	-0.598**	-2.008***	-0.442***	-0.441**	-2.009***
	(0.091)	(0.237)	(0.483)	(0.107)	(0.206)	(0.515)
ICS	-0.146*	-0.010	0.501	-0.342***	-0.419	-0.420
	(0.086)	(0.305)	(0.640)	(0.113)	(0.329)	(0.825)
MEDIAsentiment	0.499***	0.118	-0.628	0.406***	-0.060	-0.727**
	(0.090)	(0.181)	(0.401)	(0.119)	(0.173)	(0.341)
EPU	0.000	0.001	0.001	0.000	0.001	0.002
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.003)
ADS	0.023	0.624*	2.493***	0.141	1.231***	3.038***
	(0.131)	(0.353)	(0.642)	(0.130)	(0.348)	(0.859)
Ret(t)		-0.241	-0.210		-0.234	-0.279
		(0.152)	(0.238)		(0.150)	(0.291)
Ret[t - 5, t - 1]	-0.047	-0.127*	-0.366**	-0.104***	-0.084	-0.342**
	(0.033)	(0.069)	(0.155)	(0.034)	(0.074)	(0.161)
Ret[t - 21, t - 6]	-0.034*	-0.112**	-0.389***	-0.030	-0.079*	-0.417***
	(0.019)	(0.051)	(0.116)	(0.020)	(0.045)	(0.120)
Log#EA	0.059	0.076	0.180	0.052	-0.052	-0.168
	(0.060)	(0.133)	(0.238)	(0.052)	(0.138)	(0.261)
Log#AbnMessages	-0.112	-0.086	0.649	-0.204	0.064	0.989
	(0.212)	(0.505)	(0.845)	(0.215)	(0.374)	(0.866)
Observations	822	822	822	822	822	822
Adjusted R-squared	0.183	0.089	0.480	0.198	0.088	0.302