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 three 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, short sales, 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.

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1. Introduction

Social media users often use pictures or short videos to convey ideas and emotions to others. When aggregated, these dynamic visual representations can reflect the thoughts and feelings of investors that drive their trading decisions in the financial markets. Given the potentially significant influence investor sentiment may have on 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 new visual format that uses short, looping video animations to vividly convey thoughts, feelings, or stories, often with a humorous twist. [1] GIFs are widely shared across social media platforms, including those dedicated to investing. Milner and Highfield's study (2017 underscores the significance of GIFs as essential communication tools in social media, emphasizing their efficiency in conveying emotions, reactions, and cultural context through their versatile and dynamic nature. These considerations suggest that GIFs are likely well-suited as proxies for investor sentiment.

In this study, we construct a novel investor sentiment index, GIFsentiment, using GIFs to proxy the sentiment of social media communications about the aggregate stock market. We evaluate whether GIFsentiment predicts market returns, trading volume, short sales, volatility, and flows toward equity funds versus debt funds. To our knowledge, this is the first study to directly relate GIF visuals to market sentiment and stock market outcomes.

The power of GIFs as communication tools lies in their ability to capture attention and convey ideas and feelings—sometimes far more effectively than purely textual communication. By integrating motion with a sequence of images, GIFs are uniquely suited to encapsulate ideas about past events, future forecasts, mini-stories, and even cause-and-effect relationships.

[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.

Furthermore, the combination of images, motion, and humor makes them highly engaging and capable of capturing attention.[2] The salience of such features is supported by the psychology of attention and communication.

Visual formats, such as GIFs, heavily influence how people perceive and process information (e.g., Fiske and Taylor 2016). Neuroscience research (e.g., Dragoi and Tsuchitani 2016) shows that a large portion of the human cerebral cortex is dedicated to processing visual stimuli, underscoring the power of visuals in human cognition. Tech industry practitioners also emphasize the importance of multimodality for effective communication, recognizing that visuals complement text for more effective 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 associated with more extreme evaluations, enhanced long-term memory (Storbeck and Clore 2008), and increased risk-taking (FeldmanHall et al. 2016). Moreover, this physiological arousal is strongly linked to autonomic responses and impulsive decision-making (Herman, Critchley, and Duka 2018). So GIFs, by generating increased physiological arousal, may more impulsive investor decisions and less efficient market outcomes.

Vividness, as defined by Nisbett and Ross (1980), is information that is emotionally engaging, concrete and imagery-provoking, further enhances their effectiveness. Vivid

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[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.

[3] See, for example, the discussion between such as OpenAI cofounder Ilya Sutskever and Nvidia founder Jensen Huang in Highlights of the Fireside Chat with Ilya Sutskever & Jensen Huang: AI Today & Vision of the Future (youtube.com) at 00:23:47 or https://www.nvidia.com/en-us/on-demand/session/gtcspring23-s52092/.

information is more likely to capture attention and be remembered, and to influence attitudes compared to abstract or prosaic.

GIFs are also more succinct than text or still images. This brevity enhances the emotion intensity and appeal of a message, a phenomenon highlighted by Potter et al. (2014). GIFs offer a unique immediacy of experience, being instantly understandable and effective at expressing emotions and telling stories. Bakhshi et al. (2016) found that GIFs are more engaging than text or static images for these reasons. Given the overwhelming amount of information available to investors with limited attention spans, these features of GIFs make them an efficient way to communicate and capture sentiment.

Finally, GIFs also have the ability to depict sequences of event, 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 towards the moon can be used to represent an anticipated rapid rise in the price of a stock, thereby inducing or reflecting investor sentiment.

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 particular dynamic image (such as a rocket shooting toward the moon)—regarded as a single entity regardless of the number of times it is instantiated in postings. By counting how often each unique GIF is part of a post that is labeled bullish or bearish across all posts, we determine the net bullish sentiment for each unique GIF. Crucially, this net bullish sentiment of unique GIFs, a GIF-level measure of 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 the valence sentiment of each unique GIF by the proportion of net bullish declarations. This is the total number of bullish declarations minus the number of bearish declarations for each unique GIF, divided by the total number of appearances of the GIF. We use a forward-expanding window to avoid look-ahead bias when calculating the sentiment for each unique GIF. This approach yields a continuous net bullish sentiment measure for each unique GIF, updated daily. The daily aggregate sentiment measure, GIFsentiment, is the appearance-weighted average valence for each day, as detailed in Subsection 2.2.

Our sample period is from September 2020, when Stocktwits added a menu button to link to Giphy.com to search for a GIF, through December 2023. Giphy.com is one of the largest GIF repositories worldwide. It allows users composing posts to search for GIFs to include along with text to express their sentiments more vividly. Importantly, Stocktwits 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.

We compare the predictive ability of GIFsentiment for market outcomes with five other sentiment measures drawn from previous literature as described in Section 2.3. TEXTsentiment is the daily net sentiment of words embedded in the text body of posts, constructed using the VADER lexicon (Hutto and Gilbert 2014). SELFDEC reflects the net count of bullish versus bearish user declarations from Stocktwits posts that exclude GIFs, on a given day (see also Cookson and Niessner (2020) and Cookson, Engelberg, and Mullins (2023)). By focusing exclusively on posts without GIFs, SELFDEC isolates the unique information conveyed through self-declarations, distinguishing it from GIFsentiment.[4] BW is the monthly Baker-Wurgler sentiment measure (Baker and Wurgler 2006) obtained from Jeffery Wurgler's website. ICS is the monthly University of Michigan consumer sentiment index. MEDIAsentiment is the daily aggregated sentiment of traditional news media articles obtained from RavenPack.[5] The sentiment measures are pairwise significantly correlated, suggesting that there is commonality in what these variables capture.[6]

In our first set of tests, we estimate the associations of these sentiment measures with several proxies for mood from past literature. This tests whether investor sentiment proxies are

[4] The use of a GIF in addition to a self-declaration is likely an indicator of more intense sentiment and may also be indicative of a kind of investor who is more sentiment-driven.
[5] Studies that have used RavenPack's news article sentiment scores include Jeon, McCurdy, and Zhao (2022) and Bushman and Pinto (2024).
[6] Obaid and Pukthuanthong (2022) develop a proxy for investor sentiment based upon human ratings of still images. 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.

capturing the effects of time-variation in investor feelings. 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 ΔCOVID index for the increased stringency of government lockdown restrictions imposed in response to COVID-19 (Terry, Parsons-Smith, and Terry 2020, Bueno-Notivol et al. 2021).

Consistent with GIFsentiment capturing investor mood, we find that GIFsentiment is higher during months with rising mood and lower during months with declining mood, for days with higher cloudiness, and for days when government lockdown restrictions became stricter. The BW sentiment measure exhibits comparable patterns, indicating it may also capture investor 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 as a proxy for contemporaneous news about fundamentals. We define a firm's earnings announcement outcome as non-negative if earnings meet or beat consensus analyst forecasts. We then define aggregate earnings news as the fraction of earnings announcement outcomes that are non-negative on the given day. We find that neither GIFsentiment nor BW significantly correlates with aggregate earnings news, whereas the four other sentiment proxies are significantly correlated with it. These findings suggest that GIFsentiment may be a purer proxy for investor mood and attention than some of the other sentiment proxies, which are likely to also capture rational reactions to fundamental news.

Our main tests examine the relation of market outcomes to sentiment in relation to the predictions of 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 23 basis points on the contemporaneous S&P 500 index return, and a return that is lower by 18.6 basis points in the first week and 97.5 basis points in the first month.[7]

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), and an investor attention proxy, Log#EA for the day's number of earnings announcements (Hirshleifer, Lim and Teoh 2009). 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.

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

[7] 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.

and BW exhibits the opposite pattern of a negative relation with contemporaneous, one-week and one-month returns.

To summarize so 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 (see also 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).

So to further test the investor sentiment hypothesis, we use major US equity indices and portfolios formed based on firm size and idiosyncratic volatility. Our evidence is consistent with investor sentiment effects being captured by GIFsentiment. GIFsentiment has stronger predictive power on returns among portfolios that are likely most sensitive to psychological bias and most costly to arbitrage – highest quintile idiosyncratic volatility and the smallest quintile size portfolios.

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 (e.g., 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 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 suggest that GIFsentiment captures investor sentiment unrelated to fundamentals, whereas the other sentiment measures except MEDIAsentiment contain some information about fundamentals that helps resolve uncertainty.

We also explore the relationship 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. As hypothesized, we find a positive association of absolute GIFsentiment with trading volume.

If a sentiment measure captures mispricing, there is an incentive for arbitrageurs—traders who bet against mispricing—to respond to sentiment-associated returns. Motivated by evidence that short-selling is a negative predictor of stock returns, we use short-selling as a proxy for arbitrage activity. We find that GIFsentiment is positively associated with short sale volumes in various post-event windows. This is consistent with short selling by arbitrageurs contributing to return corrections reversals in weeks after the event.

Finally, we examine the relation between GIFsentiment and the behavior of retail investors, who are often identified with noise traders in past literature, and who hold a high fraction of U.S. mutual fund assets.[8] Our final set of tests therefore examine whether investor sentiment predicts equity and bond mutual fund flows. We use daily flows to mutual fund groups as a proxy for aggregate noise trading at the asset class level. To test for shifts in optimism, we examine flows to funds that specialize in U.S. equity or in U.S. bonds.

[8] 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.

We find that an increase in GIFsentiment forecasts a substantial inflow into equity funds and a substantial outflow from bond funds on the same day and the following week. Given our findings that high GIFsentiment is associated with higher subsequent volatility, this might be called a "flight from safety" effect, which provides a sharp contrast with "flight to safety" effects considered in past research (Baele et al. 2020). Investors presumably do not inherently like high risk, but may be drawn to it by high sentiment.

Our return predictability and related findings indicate that GIFsentiment captures attention or feelings more sharply than do other sentiment measures from past literature. Unlike the alternative sentiment measures, GIFsentiment strongly correlates with mood proxies suggested by past literature. In contrast, several alternative sentiment measures lack consistent correlations with mood proxies and are instead correlated with proxies for past fundamental news. Furthermore, GIFsentiment negatively predicts returns over the subsequent month, which is not the case for some alternative proxies for sentiment,

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), and 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 ways a sharper sentiment proxy from several used in past 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. (2024) 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 research on predictability of the aggregate stock market uses several characteristics, such as aggregate dividend yield, to predict market returns. A number of papers on investor mood or sentiment also find aggregate return predictability.[9] Our paper differs in that it develops a measure that reflects sentiment as expressed by investors in their communications with other investors, and it does so through dynamic visuals to capture fluctuations in mood and attention. This social transmission feature gets more directly at what is arguably an important aspect of investor sentiment, that it can spread from person to person rather than just by investors reacting in isolation to news in mass media.[10]

2. Sentiment Measures and Mood Proxies

We next describe our sentiment measures and mood proxies. Subsection 2.1 contrasts GIFsentiment with sentiment measures from previous literature. Subsection 2.2 describes the detailed construction of GIFsentiment. Subsection 2.3 describes the measurement of other sentiment variables used as controls in our tests, and Subsection 2.4 describes mood proxies from past literature. In Subsection 2.5, we validate GIF sentiment as a plausible sentiment measure by evaluating its association with mood proxies from past literature.

2.1 Existing sentiment proxies

[9] Hirshleifer and Shumway (2003) find that cloud cover predicts market returns at a one-day horizon. Edmans, Garcia, and Norli (2007) find that sports sentiment predicts returns at a one-day horizon. Ben-Rephael, Kandel and Wohl (2012) document that net flows to equity over bond funds negatively predict market returns at a horizon of 10 months. Da, Engelberg, and Gao (2015) use daily Google search volume as a proxy for market-level sentiment. They find that a proxy for investor fear predicts returns positively at a horizon of two days. Huang et al. (2015) find that a sentiment measure that combines 6 proxies for investor sentiment in a statistically optimal fashion predicts returns one-month-ahead stock returns. Obaid and Pukthuanthong (2022) find that a proxy for investor sentiment based on human ratings of news photos predicts aggregate market returns up to a horizon of one week. Mai, Hirshleifer, and Pukthuanthong (2024) provide evidence that war discourse in the news media predicts returns at horizons of up to 36 months, though such effects could derive from risk or mispricing.

[10] 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.

To quantify investor sentiment, past studies have used surveys, combinations of economic variables, and textual analysis from various content sources to forecast firm-level or aggregate stock market returns and other outcomes. As discussed in Section 2.4, other studies use event shocks from morning sunshine (Hirshleifer and Shumway 2003) and sports victories and defeats (Edmans, Garcia, and Norli 2007) as proxies for investor mood, an aspect of sentiment.

Survey sentiment measures include the Michigan Consumer Index (Qiu and Welch 2004), and the American Association of Individual Investors (AAII) monthly sentiment survey, which asks individual investors about their bullish, bearish, or neutral outlook for the next six months. A classic sentiment measure based on economic variables is by Baker and Wurgler (2006). They construct their sentiment index from the first principal component of six economic proxies – NYSE turnover, the dividend premium, the number of IPOs, the first-day returns on IPOs, the closed-end fund discount, and the equity share in new issues. Ben-Rephael, Kandel and Wohl (2012) find that monthly aggregate net exchanges to equity funds are contemporaneously correlated with aggregate market returns that reverse within ten months, consistent with fund flows reflecting investor sentiment.

Textual sentiment measures have been constructed using sources such as media articles, financial reports, or posts on social media websites. These measures often quantify sentiment as word frequencies or frequencies of directly 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 general issue for deriving sentiment measures from the analysis of social media text or visuals is ecological validity—does the social media context match the investing context? For example, a general platform such as Twitter reflects the public at large, including individuals with limited interest in actively trading stocks. Many participants do not participate in the stock market at all. Furthermore, Amazon Mechanical Turk raters work for very low pay to construct a sentiment measure, implying a relatively low likelihood of participating in the stock market. So, a machine learning sentiment measure that trains on Twitter photos using Amazon Mechanical Turk raters has a mismatch with the stock market investing context that is the focus of investor sentiment measures.

Impressively, despite this challenge, Obaid and Pukthuanthong (2022) find that a visual sentiment proxy using such an approach predicts aggregate returns in the following week from trading days t + 1 to t + 5.[11] Their daily pessimism index is constructed using the proportion of static photos of negative images to proxy for negative sentiment in the *Wall Street Journal* (*WSJ*). They use a dataset of 882 photos from Twitter as their training set in their ML model to classify sentiment of photos in 148,823 WSJ articles. Their findings suggest that an approach with greater context matching may be even more powerful in capturing market sentiment.

Our approach minimizes context mismatch by applying the natural environment of Stocktwits.com and labeling sentiment for the GIFs directly from bullish or bearish post declarations by the posters themselves. These are likely individuals actively participating in or interested in the stock market, and their self-declarations serve as 'ground truth' labels for sentiment, ensuring ecological validity.

This approach also avoids two other limitations of employing raters noted by Saravanos et al. 2021; Aguinis, Villamore, and Ramani 2021): the high cost of annotation, which constrains the size of training samples, and the unrepresentativeness of annotators. In many studies, external raters are Amazon Mechanical Turk workers or undergraduate research assistants, who have limited incentives and limited expertise about the stock market, and therefore unrepresentative of stock investors.

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

We test whether GIF sentiment is incrementally associated with stock market outcomes based on several sentiment measures in the literature, including text-based sentiment, Baker-Wurgler sentiment, the Michigan Consumer Index, and traditional media sentiment. We describe the construction of these alternative sentiment measures in Subsection 2.3.

Several other studies examining the relation of visual content to the stock market, typically at the level of individual firms (Blankespoor, Hendricks, and Miller (2017), Nekrasov, Teoh, and Wu (2022), Peng et al. (2022), Christensen et al. (2023), and Ronen et al. (2024)).[12] These studies test how static visuals in corporate communications shape investor perceptions about firms or stock market investing decisions. Our study focuses on the predictive relation between sentiment obtained from dynamic visual representations for aggregate stock market outcomes.

2.2 GIF sentiment

At its launch in 2008, Stocktwits.com users could post text and hyperlinks on the platform. Beginning in September 2020, users were enabled to supplement the text in their posts with a GIF using a menu button. Clicking on the GIF button activates a link to Giphy.com, the largest global GIF search engine, allowing users to select a GIF conveniently to express themselves more fully.

Several features of Stocktwits posts facilitate the construction of a high-frequency sentiment measure from the posts. Each post has a date and time stamp, so a daily sentiment measure is feasible. Users can use a cashtag, which consists of a dollar sign followed by a stock ticker symbol (e.g., $AAPL for Apple Inc.), to specify the stock they are referring to in a post. If the discussion involves multiple stocks, users can include several cashtags. This feature helps us

[12] 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. (2023) explore the types and placement of infographics in 10-K filings, examining factors influencing their usage and persistence over time. Ronen et al. introduce a machine learning-based measure to quantify the informativeness of images on equity crowdfunding pitch webpages, and linking image characteristics to fund investment decisions.

accurately identify that the posting is about a stock or stocks (which is also potentially indicative of attention to the equity market more broadly).

Conveniently for research on dynamic visuals, Stocktwits posts that include a GIF are identified by their URLs ending in .gif, and each GIF has a unique identifier recorded by Giphy.com.[13] These features enable accurate identification of unique GIFs. Our sample includes 65 million posts with either single or multiple cashtags[14] between September 1, 2020, to December 31, 2023. Of these, 4.2 million posts have visuals, and 468,306 GIFS are unique.

In September 2012, Stocktwits introduced a feature allowing users to declare their posts as either bullish or bearish using a menu button. We build on previous studies (e.g., Cookson and Niessner 2020, Cookson et al. 2023) that use these declarations in posts as a proxy for the sentiment of the post. Our approach differs in using self-declarations in posts that contain both self-declarations and GIFs to ascertain the sentiment of other posts that do not contain self-declarations. During our sample period, every unique GIF had at least one declaration of sentiment so we were able to label all unique GIFs.[15] By aggregating declarations of optimism and pessimism across multiple posts with self-declared sentiment, we calibrate the sentiment - positive or negative - associated with each unique GIF.

Specifically, we calculate the sentiment of each unique GIF *j* by subtracting the total number of bearish declarations from the total number of bullish declarations and dividing by the total number of appearances for GIF *j*. To avoid look-ahead bias, we employ a forward-expanding window when calculating the sentiment of unique GIFs, resulting in a daily measure. This

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[13] 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.

[14] Prior 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.

[15] Our sample contained 31.8 million posts with bullish/bearish declarations, and 13% (4.2 million) of them include GIFs yielding 468,306 unique GIFs in our sample period. The reported results are robust to requiring that each unique GIF's sentiment be calculated from at least 5 self-declarations of bullish or bearish sentiment.

continuous sentiment measure, Unique GIFsentiment, is applied to each unique GIF on a daily basis. Table A1 reports the scores for the 25 GIFs with the highest sentiment and the 25 GIFs with the lowest sentiment during our sample period. The daily aggregate GIFsentiment measure, *GIF sentiment*, depends on both the intensity of positive or negative sentiment of the unique GIF and the frequency of the GIF's appearances on a particular day. The measure is obtained by weighting the unique GIFsentiment scores by their appearance frequency each day, as follows:

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

where $\#Appearance_{j,t}$ is the total number of posts for GIF *j* on day *t*, $\#Posts_t$ is the total number of posts on day *t,* and $Unique\ GIFsentiment_j$ is the proportion of the net bullish sentiment declarations of GIF *j* on day *t*.

2.3 Alternative sentiment measures

To evaluate the incremental association of our GIFsentiment measure with stock market outcomes, we control for a wide set of sentiment measures from past literature. These include the Baker-Wurgler sentiment, the University of Michigan Consumer Sentiment Index, traditional media sentiment, sentiment extracted from the textual content of Stocktwits posts, and self-declared sentiment on Stocktwits.

The Baker-Wurgler (BW) index is a broad-based measure of speculative sentiment derived using a principal components analysis of six market-wide indicators discussed in Section 2.1. It is only available monthly. The values of the monthly indicators are obtained from the month preceding the month of the GIFsentiment score.

The Michigan Consumer Sentiment Index (ICS) is a survey-based measure of consumer confidence that reflects public perceptions about the economy and financial conditions. It is also available only at a monthly frequency from the University of Michigan's Surveys of Consumers or from the Federal Reserve Bank of St. Louis FRED (Federal Reserve Economic Data) website.

As with the BW monthly variable, we also use the ICS indicator in the preceding month to the GIFsentiment score.

Various text-based sentiment measures have also been applied in previous research.[16] Following Tetlock (2007), we include a traditional news media sentiment measure, MEDIAsentiment, for comparison and control. RavenPack provides this daily sentiment measure to capture the tone of the financial news media that day. They employ a proprietary machine learning model and AI technology to code sentiment based on words used in the news media articles.[17]

We control for two further sentiment measures constructed from the Stocktwits posts themselves. The first is a daily aggregate textual sentiment measure (TEXTsentiment) obtained by employing the Valence Aware Dictionary and Sentiment Reasoner (VADER) developed by Hutto and Gilbert (2014) to the daily Stocktwits posts and calculating a daily average.[18]

The second StockTwits sentiment measure is constructed from declarations of bullish or bearish sentiment directly by the authors of the Stocktwits posts themselves, as described in the preceding subsection. Using such declarations, Cookson and Niessner (2020) examine investor disagreement, and Cookson, Engelberg, and Mullins (2023) document an echo chamber phenomenon. These papers find that variables based upon self-declarations predict individual stock returns or trading volumes.

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[16] Tetlock (2007) construct a media pessimism index by counting the number of negative words in the text of the Wall Street Journal column "Abreast of the Market." Loughran and McDonald (2011) construct a sentiment measure using positive or negative words in financial reports. Da, Engelberg and Gao (2015) build a FEAR index using Google search terms for recession, unemployment, foreclosure and bankruptcy. Chen et al. (2014) build a sentiment measure by calculating the frequency of negative words in articles and commentaries on Seeking Alpha. Renault (2017) and Giannini, Irvine, and Shu (2018) both construct measures of text sentiment from social media platforms—Stocktwits and Twitter, respectively—and study their relations with stock returns and trading volume.

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

[18] 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.

Our interest is in studying the incremental forecasting power of GIFsentiment over other sentiment measures. To construct a benchmark measure of sentiment associated with declarations as distinct from sentiment associated with GIFs, we construct a SELFDEC sentiment measure using only declarations in posts *without* GIFs. Specifically, SELFDEC is defined as the difference between the total number of bullish declarations and the total number of bearish declarations from all *non*-GIF posts for each day divided by the total number of all non-GIF posts that day.

To facilitate comparisons, we standardize all six sentiment measures to have zero mean and unit variance. Table 1 summary statistics for the variables indicate that the sentiment measures are correlated with each other, the strongest correlations GIFsentiment is with TEXTsentiment, BW, and SELFDEC.

2.4 GIFsentiment and mood

Several studies have proposed proxies for investor mood and have provided evidence that such proxies are associated with stock market returns. According to past studies, for the United States, January is associated with the improving mood of the New Year period, and March is associated with the highest recovery from seasonal affective disorder (SAD). In contrast, September and October are associated with the onset of SAD. Following this literature, we use a positive mood indicator for months January and March, and a negative mood indicator for months 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).

Hirshleifer and Shumway (2003) find that cloudy weather is associated with lower aggregate stock returns in tests across 26 countries. Following Goetzmann et al. (2015) and Edmans et al. 2022), we collect hourly sky cloud cover data from the National Oceanic and

Atmospheric Administration website (NOAA)[19] and calculate the average daily cloud cover (DCC) by using the hourly values from 6 a.m. to 12 p.m. across the country's different weather stations. Following Hirshleifer and Shumway (2003), to focus on cloudiness rather than other seasonal effects, we deseasonalized the cloud cover measure by subtracting each week's mean cloudiness from each daily mean.

Recent studies provide evidence that COVID-19 pandemic restrictions adversely affected mood (Terry, Parsons-Smith, and Terry 2020, Bueno-Notivol et al. 2021, Edmans et al. 2022). If such restrictions demoralized investors, we expect that GIFsentiment to be lower when stronger restrictions were imposed. Following past studies, we construct an index based on lockdown restrictions compiled by the University of Oxford's COVID-19 government response tracker.[20]

2.5 Sentiment and mood proxies

To evaluate whether our GIF construct is a proxy for sentiment, we test whether it is associated with seasonal mood patterns, weather-induced mood, and COVID restrictions by estimating the following panel regression:

$$\begin{aligned} GIFsentiment_t = {}& \alpha + \beta_1 Positive\ Months_t + \beta_2 Negative\ Months_t + \beta_3 DCC_t \\ & + \beta_4 COVID\ Index_t + \varepsilon_t. \end{aligned} \tag{2}$$

Here, *Positive* Months is an indicator variable that equals 1 for January and March and 0 otherwise; *Negative Months* is an indicator that equals 1 in September and October and 0 otherwise. *DCC* is the deseasonalized average daily cloudiness. *COVID Index* is the daily measure of the stringency of the government's response to COVID. We estimate Equation (2) using ordinary least squares

[19] 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).

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

(OLS) and calculate Newey-West *t*-statistics, which are robust to heteroscedasticity and autocorrelation. Table A2 lists the definitions and sources of the variables.

Table 2 Panel A reports the regression estimates. Consistent with GIFsentiment capturing investor mood, column 1 shows that GIFsentiment is positively associated with positive mood periods (*Positive Months*), and is negatively correlated with negative mood periods (*Negative Months*), daily cloud cover (DCC), and more stringent lockdown restrictions (COVID Index).

For comparison, we also assess whether five alternative sentiment measures capture mood by estimating Equation (2) with TEXTsentiment, SELFDEC, BW, ICS, and MEDIAsentiment as dependent variables. Columns 2 to 6 in Table 2 Panel A indicate that, except for BW, these sentiment measures are not associated with mood proxies in the predicted directions. TEXTsentiment is negatively correlated with periods of uplifted mood, while SELFDEC, ICS, and MEDIAsentiment are positively correlated with the stringency of COVID-19 lockdown restrictions. Additionally, SELFDEC and ICS are not significantly associated with daily average cloudiness.

We next examine the relation between the six sentiment proxies and economic fundamentals. Although not a requirement for a sentiment measure, a low correlation with fundamentals suggests that a sentiment measure reflects imperfect rational variation in investor attitudes in a relatively pure way, as contrasted with variation derived from rational reactions to news.

We, therefore, estimate the relations between these three sentiment measures and a fundamental proxy, the percentage of earnings news outcomes that are positive for firms whose earnings announcements fall on the focal date *(%PositiveEANews*). We define non-negative earnings news as meeting or beating consensus analyst forecasts. For companies mentioned by cashtag ($) in our sample, we compute a daily percentage by dividing the number of firms that announced non-negative earnings news by the total number of firms announced earnings on day *t*.

Results in Panel B of Table 2 indicate that SELFDEC, ICS, and MEDIAsentiment are significantly positively associated with *%PositiveEANews* at the 1% level, suggesting that these proxies may be contaminated by meaningful information content. In contrast, GIFsentiment and BW is not significantly correlated with the information proxy. These results, together with those in Table 2 Panels A, suggest that visual-based GIFsentiment reflect mood-driven sentiment rather than rational responses to fundamental news.

Several past sentiment measures focus on pessimism and/or find an association with negative market outcomes (Tetlock (2007), Chen et al. (2014), Da, Engelberg and Gao (2015), Obaid and Pukthuanthong (2022) and Edmans et al. (2022)). While negative news generates greater media attention, in the contemporary landscape of social media and digital communication, high arousal positive content messages can also go viral (Berger and Milkman (2012). There is a tendency for people to upvote or retransmit more positive messages (Kramer, Guillory, and Hancock 2014, Rosenbusch, Evans, and Zeelenberg 2019, Goldenberg and Gross 2020). To examine whether GIFsentiment can proxy for optimism and pessimism, we also construct separate positive and negative aggregate GIFsentiment using unique GIFs with only positive and negative sentiment, respectively, and include both in an additional test.

3. Sentiment and stock returns

We examine the relation between GIFsentiment and contemporaneous daily returns on the aggregate CRSP value-weighted S&P 500 market index and test the ability of GIFsentiment to forecast future daily returns over various windows. We examine both *GIFsentiment* individually and also jointly with the five other sentiment measures from past research to evaluate its incremental explanatory power.

To test behavioral model predictions that net sentiment positively predicts future short-term stock returns and negatively predicts longer-term returns, we run the regression:

$$\%Ret_{(t+m,t+n)} = \alpha + \beta\ Sentiment_t + \gamma\ Controls_t + \varepsilon_t, \quad (3)$$

where $\%Ret_{(t+m,t+n)}$ represents either the day t contemporaneous return, the cumulative returns over the first week from days ($t + 1$, $t + 5$), and over the month from days ($t + 1$, $t + 20$). $Sentiment_t$ is GIFsentiment$_t$ in the regressions with a single sentiment measure only, and is a vector that includes the five other sentiment proxies, TEXTsentiment, SELFDEC, BW, ICS, and MEDIAsentiment in regressions on all sentiment measures jointly (with β a vector in that case). The sentiment measures are standardized to have zero mean and unit variance to facilitate comparing across measures.[21] The behavioral approach predicts a positive coefficient for contemporaneous return on day t and a negative coefficient for subsequent weekly and monthly returns.

Following past studies (Da et al. 2014, Edmans et al. 2022), we control for daily news-based measures of U.S. economic policy uncertainty, EPU, developed by Baker, Bloom, and Davis (2016).[22] We also control for daily U.S. macroeconomic activity using the Aruoba et al. (2009) index, ADS, from the Federal Reserve website,[23] we control for past returns, %Ret[-5, -1] and %Ret[-21, -6], and daily Log#EA to remove aggregate return reversal and possible investor distraction effects. As the sentiment measures may be serially correlated, we correct for potentially biased t-statistics using the Nelson and Kim (1993) procedure to calculate randomized p-values.[24]

3.1 Sentiment association with stock market returns

Table 3 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

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[21] A Variance Inflation Factor (VIF) test to diagnose potential multicollinearity among three sentiment measures show that VIF values range between 1.5 to 2. Thus, multicollinearity is not a concern.

[22] 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.

[23] 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.

[24] We also computed bootstrapped standard errors. The results are robust.

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, and lagged returns. 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 magnitudes of the GIFsentiment coefficients are economically substantial; a one standard deviation increase in GIFsentiment increases same-day market returns by 23 basis points, which is followed on average by a return of −18.6 basis points in the subsequent week or −97.5 basis points in the subsequent month. This last result translates to an annualized −12.3% return reversal within one month, which is economically substantial.[25]

It might seem surprising for a subsequent correction to exceed in magnitude the contemporaneous reaction to a sentiment measure. However, this is entirely possible in a behavioral setting in which high sentiment is positively associated with preexisting overpricing as well as a new contemporaneous increment to mispricing. Indeed, as mentioned earlier, sentiment measures tend to be positively serially correlated, consistent with serial correlation in sentiment and mispricing. Our test statistics address the serial correlation using standard adjustments and randomized/bootstrapped p-values.

Panel B indicates that the GIFsentiment results are also robust and incremental to controlling for other sentiment proxies. The magnitudes are slightly smaller compared to Panel A; a one-standard-deviation higher GIFsentiment is associated with an 18.5 bp higher same-day return and a 70.7 bp lower return over the subsequent month, both significant at the 1% level. Controlling for other sentiment variables does not remove the explanatory and forecasting power of

[25] GIFsentiment predicts negative returns for approximately one to four weeks ahead in our sample, with more substantial predictability than is found using other recent sentiment measures. For comparison, Obaid et al. (2022) find −10 bps (−5.8% annualized) over the subsequent 1 week, Edmans et al. (2022) find −7 bps (−3.7% annualized) over the subsequent 1 week, and Da et al. (2014) find −14 bps (−19% annualized) over the subsequent 2-days.

GIFsentiment. GIFsentiment is positively correlated with lagged returns in the immediate prior week. Together these results suggest that GIFsentiment is a good incremental proxy for identifying past market overvaluation that is corrected during the month after the sentiment conditioning date.

Unlike GIFsentiment, none of the other sentiment proxies in Panel B display incremental behavior consistent with the predictions of investor sentiment theory. For example, TEXTsentiment is positively incrementally associated with day 0 returns, but it does not negatively predict the future one-month return. BW is incrementally associated with all three window returns, but in the opposite direction predicted from sentiment theory.[26] SELFDEC and MEDIAsentiment are positively associated with day 0 returns but do not predict subsequent negative returns. The positive predictive power of TEXTsentiment for longer-horizon returns suggests that TEXTsetiment may contain information about long-term fundamental value. The significant negative day 0 coefficient for ICS is the opposite sign of the prediction of the investor sentiment model. In sum, GIFsentiment is incrementally superior as a proxy for sentiment to the other five sentiment measures.

In additional, unreported tests, we separately examine the impact of positive and negative GIFsentiment proxies on returns. Optimistic GIFsentiment is derived from GIFs with a net positive unique sentiment score, while pessimistic GIFsentiment is based on GIFs with a net negative unique sentiment score. When both optimistic and pessimistic GIFsentiment scores are included in the regression equation (3), both proxies demonstrate similar results as before. However, return reversals take longer for optimistic GIFsentiment (within one month), whereas pessimistic GIFsentiment shows negative returns within one week.

We perform several robustness checks to see whether potential outliers in the returns-based dependent variables or GIFsentiment influence our main findings or whether the findings are sensitive to the market index used. First, we winsorize the return measures at the top and bottom

[26] This may derive from the fact that BW builds upon proxies observed at monthly rather than daily frequencies.

1%, 5%, or 10%, and we find similar results for GIFsentiment. Second, we exclude Stocktwits posts of 50 meme stocks[27] when constructing the GIFsentiment measure, and we find similar results. Third, we examine the post-estimation statistics DFBETA, which measures how much each observation affects a particular predictor. The analysis identifies 27 days in our sample with large DFBETA values. Excluding these 27 days from the sample when estimating Equation (3) yields similar results. Overall, our main findings are not influenced by outliers. We also find that the GIFsentiment-return relations are robust to using the returns of five alternative 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*).

3.2 GIFsentiment and susceptibility to mispricing

We perform further tests to see if the return forecasting power of GIFsentiment is stronger among stocks that have greater mispricing pressure or tighter limits to arbitrage. To do so, we examine the relation between GIFsentiment and both immediate returns and long-term reversals across stock portfolios that differ by size and stock idiosyncratic uncertainty. Several factors can modulate the effect of investor sentiment on asset prices. Specifically, Kumar (2009) finds that individual investors exhibit stronger biases for stocks with higher uncertainty. Pontiff (1996) provides evidence, and Shleifer and Vishny (1997) providing modelling indicating that mispricing is higher when limits to arbitrage are tighter. Small stocks are particularly risky and costly to arbitrage. Furthermore, they tend to be held disproportionately by retail investors, suggesting that they will be more prone to mispricing pressure (Lee, Shleifer and Thaler 1991).

Motivated by these insights, we study differences in the relation between GIFsentiment and both contemporaneous and future returns of stock index portfolios that focus on different categories of stocks. First, we sort stocks into quintile portfolios based on the firm's market

[27] We use 50 stocks that faced restrictions by Robinhood app on January 28th, 2021 during the GameStop episode.

capitalization. Past literature shows that the association between sentiment and stock market returns is stronger for smaller stocks (e.g., Baker and Wurgler 2006, Edmans et al. 2007). Hence, we expect GIFsentiment return reversals to be stronger for a portfolio of small stocks than for a portfolio of large stocks.

Second, we sort stocks into quintile portfolios based on idiosyncratic volatility estimated with the Fama-French five-factor model using the past 36-month returns. We hypothesize that the association between GIFsentiment and portfolio returns will be stronger for a portfolio consisting of stocks with higher idiosyncratic volatility, consistent with findings by Wurgler and Zhuravskaya (2002) and Baker and Wurgler (2006). Similarly, we examine the differences between the top and bottom total return volatility groups, hypothesizing that the sentiment effects on returns are stronger for the high return volatility group (Wurgler and Zhuravskaya 2002).

To test these hypotheses, we estimate Equation (3) separately for the Small Cap, bottom quintile size, group and the Large CAP, top quintile, size group (2) the High, top quintile idiosyncratic risk group and the Low, bottom quintile idiosyncratic risk group and (3) the HighVol, top quintile return volatility group, and the Low, bottom quintile return volatility group. The results are reported in Table 4.

Columns 1 to 3 in Panel A1 columns 1 to 3 report the results for the Small group, and columns 4-6 for the Large group. The results show that GIFsentiment is positively and significantly correlated with small minus large-cap index returns spread on day 0 and has a negative and borderline significant relation with the size returns spread over the subsequent one month. A one-standard-deviation greater GIFsentiment corresponds to a 20.8 basis points higher return on day 0 and 85.1 basis points lower return in the following month for the Small-cap group relative to the Large-cap group.

Panel A2 reports similar results, including the five additional sentiment measures in the regressions. The relation between GIF sentiment and the size return spread on day 0 becomes insignificantly positive, while the association over the subsequent month is significantly negative. A one-standard-deviation increase in GIF sentiment corresponds to a 154.7 basis point lower return spread over the following month. Overall, the results indicate that the relation between aggregate GIF sentiment and returns is more pronounced among smaller stocks.

In Panels B1 and B2, a comparison of columns 1 to 3 for High idiosyncratic volatility with columns 4 to 6 for the Low group, respectively, indicates that GIFsentiment relation with day 0 and one-month post-returns is stronger for the High group than the Low group. One standard deviation greater GIFsentiment corresponds to a 42.8 basis point higher return on day 0 and 281 basis point lower returns spread over the subsequent month in Panel B2. The results are similar in columns 4 to 6 after including five additional sentiment measures in the regression. GIFsentiment shows a positive relation with the idiosyncratic volatility return spread on day 0 and negatively predicts returns over the following month.

Similar results are obtained in Panels C1 and C2, where the groups are now the top and bottom total return volatility quintiles. The High volatility group experiences higher day 0 returns and lower one-month subsequent returns than the Low volatility group.

3.3 GIF sentiment as an indicator of stock market volatility

Theoretical models imply that investor sentiment and noise trading can also increase the volatility of asset prices (Black 1986, De Long et al. 1990). For example, investors trading based on noise induces random deviations from fundamentals. To investigate such effects, we estimate the association between the absolute GIFsentiment measure and stock market volatility from days t through t + 15. We consider absolute GIFsentiment because unusually high or low sentiment can indicate heavy sentiment-based trading. We measure the volatility ($\%Volatility_{[t,t+15]}$) as the standard deviation of daily S&P 500 index returns from days 0 through 15. We also examine return volatility over two sub-periods: from day $t + 1$ to $t + 5$, and from day $t + 6$ to $t + 15$, aligning with the windows used in our return tests. To test this hypothesis, we estimate the following regression:

$$\%Volatility_{[t,t+1\ ]} = \alpha + \beta\ |Sentiment_t| + \gamma\ Controls_t + \varepsilon_t, \qquad (4)$$

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

Table 5 reports the results. We find that absolute GIFsentiment at day t positively and significantly forecasts return volatility in the subsequent week ($t + 1$ to $t + 5$). In Column 1, a one-standard-deviation greater absolute GIFsentiment is associated with a 5.6% higher in stock market volatility, which is 10.7% of the standard deviation of weekly volatility of 0.524.[28] The results are even stronger in Column 2 when the five other sentiment proxies are included in the regression.

Furthermore, absolute TEXTsentiment and absolute SELFDEC at day t are negatively and significantly correlated with stock market volatility over the following week. These negative associations suggest that these measures may provide fundamental information that helps resolve uncertainty, thereby leaving less uncertainty to be resolved in the subsequent week.

Our volatility findings together paint a consistent picture that visual-based GIFsentiment captures investor mood or attention-induced biases in expectations, leading to stock price deviations from fundamentals and excess volatility. In contrast, TEXTsentiment and SELFDEC capture fundamental information to a greater extent than mood.

3.4 GIF sentiment and trading activity

We next examine the relationship between GIFsentiment and measures of trading activity—unsigned volume of trade and short selling activity.

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

3.4.1 GIF sentiment and unsigned total trading volume

According to behavioral models (De Long et al. 1990), sentiment shocks can lead to disagreement between rational and noise investors, driving increased trading activity. Consistent with this theory, Campbell et al. (1993) find that such disagreement results in higher trading volume. If GIFsentiment reflects these dynamics, we expect extreme levels of sentiment – either high or low – to correspond to increased trading activity as the market absorbs these orders. Conversely, if GIFsentiment proxies for transaction costs, we expect a negative relationship between GIFsentiment and trading volume, as Tetlock (2007) suggested.

We therefore test whether GIFsentiment is associated with market trading activity. Table 6 explores the relation between aggregated SPX trading volume and GIFsentiment to determine whether GIFsentiment acts as a proxy for transaction costs or reflects investor beliefs. We run the following regression following Tetlock (2007):

$$LogTotalVol_{t+m\rightarrow t+n} = \alpha + \beta\,|Sentiment_t| + \delta\,Controls_t + \varepsilon_t, \qquad (5)$$

where LogTotalVol represents the natural logarithm of one plus total SPX trading volume on day t, during $t + 1$ to $t + 5$, and $t + 1$ to $t + 15$. $|\mathrm{Sentiment}_t|$ is the absolute value of GIFsentiment after it is standardized to a mean of zero. High values of $|\mathrm{Sentiment}_t|$ indicate days with unusually large positive or negative sentiment.

Table 6 Panel A columns 1 to 3 report positive and significant coefficients for $|\mathrm{Sentiment}_t|$ on day t and the subsequent month ($t + 1$ to $t + 20$), indicating that either high or low values of GIFsentiment are associated with increased trading volume. In terms of magnitude, a one-standard-deviation higher GIFsentiment is associated with 0.048 higher log trading volume on day t, which is 12% of the standard deviation of log trading volume on day t. Additionally, a one-standard-deviation higher GIFsentiment is associated with 0.009 higher log trading volume on during $t + 1$ to $t + 20$, which is 3% of the standard deviation of log volume during this period.

The results remain similar after including five additional sentiment measures. Overall, our evidence on unsigned trading volume is consistent with the behavioral explanation.

3.4.3 GIF sentiment and short sale volume

We next investigate the relation between GIFsentiment and future short selling activity. When GIFsentiment is high, speculative arbitrageurs may take advantage of negative return predictability by short selling that security (e.g., Chen and Singal 2003). Hence, we hypothesize that high GIFsentiment will forecast an initial increase in short sale volume. To test this hypothesis, we run the following regression:

$$LogShortVolume_{t+m \to t+n} = \alpha + \beta\ Sentiment_t + \gamma\ Controls_t + \varepsilon_t, \quad (6)$$

where LogShortVolume denotes the natural logarithm of one plus daily aggregate short volume. Daily short volume data is acquired from Chicago Board Options Exchange (CBOE) Global Markets. Short volume represents the number of shares sold short on a specific trading day. We consider LogShortVolume in three alternative windows, on day t, during $t + 1$ to $t + 5$, $t + 1$ to $t + 15$, to estimate short-term association and long-term predictability. The control variables are as before and also include lagged short volume ($\mathrm{LogShortVolume}_{t-1}$).

Table 6 Panel B shows that the coefficients on the short volume variables are also significantly positive in columns 1 through 3 for day 0, one week ahead, and one month ahead. Specifically, a one-standard-deviation higher GIFsentiment is associated with 0.034 higher log short volume on day 0, 0.046 for the subsequent one week, and 0.037 for the subsequent one month. These increases correspond to 8.9%, 12.1%, and 9.7% of the standard deviation of log short volume during these periods, respectively. In columns 4 to 6, short volume is not incrementally larger when other sentiment proxies are added except for the one-month short volume, which remains significantly positive at 10% level. Specifically, a one-standard-deviation increase in GIFsentiment is associated with a 0.029 increase in log short volume over the subsequent month—equivalent to 7.6% of that period's standard deviation. Overall, the short volume results are generally consistent with the finding of lower market returns during $t + 1$ to $t + 20$, suggesting that the higher short volume may be one of the drivers of the return reversal.

Table 6 Panel B shows that other sentiment measures do not exhibit the same pattern with short volume as observed for GIFsentiment. TEXTsentiment and MEDIAsentiment are negatively associated with log short volume on day t, and the subsequent week and month. This suggests that text and media sentiment may be capturing fundamental good news, reducing short selling pressure. This pattern is generally consistent with text sentiment's positive return associations in Table 3 Panel B. MEDIA sentiment, however, is only positively associated with returns on day 0. BW and ICS are positively related to log short volume, aligning with their negative return evidence in Table 3 Panel B.

3.5 GIF sentiment and fund flows

If sentiment affects investor decisions, we expect it to influence mutual fund investing as well as trading in individual equities. Such effects may be important, as individual investors hold about 95% of long-term U.S. mutual fund total net assets (Investment Company Institute 2023). Additionally, daily flows to mutual fund groups likely aggregate at the asset-class level (Ivković and Weisbenner 2009). We estimate the predictive power of GIFsentiment for daily mutual fund flows for two groups of mutual funds that specialize in U.S. equity and U.S. bonds. It has been hypothesized that when investor sentiment is low, investors move from risky to safe assets such as the bond market in a "flight to safety" (Baker and Wurgler 2012, Da et al. 2015), and the opposite when investor sentiment is high (see the evidence of Edmans et al. (2022)). Hence, we hypothesize that GIFsentiment positively predicts net equity fund flows and negatively predicts net bond fund flows.

Our daily equity and bond fund flow data are obtained from EPFR Global, a private company tracking the performance and asset allocation of a vast number of equity and debt mutual funds domiciled in developed and emerging markets. As of 2024, the EPFR global collected information from more than 151,000 share classes and 50,000 individual bonds, comprising more than $55 trillion in assets tracked in developed, emerging and frontier markets (EPFR Product Overview 2024). Daily equity and bond flows are computed as the ratio between dollar flow and fund total net assets (TNA). We then estimate the following regression:

$$EFF_{t\,+\,m \to t+n} \text{ or } BFF_{t\,+\,m \to t+n} = \alpha + \beta\, Sentiment_t + \gamma\, Controls_t + \varepsilon_t, \qquad (7)$$

where EFF represents the net fund flows equity fund and BFF represents the net fund flows for bond fund. Controls are our previous controls. To remove the seasonality in daily fund flows, we first regress EFF and BFF on day-of-week and month-of-year dummies and then use the corresponding residuals as the dependent variables for Equation (7). The results of these regressions are reported in Table 6 Panel A for equity fund flows and Panel B for bond fund flows.

In Panel A, the results show that GIFsentiment is positively correlated with mutual fund flows on day 0 and during $t + 1$ to $t + 5$. After including five additional sentiment measures in the regressions, the results remain similar. In terms of the magnitude, a one-standard-deviation higher GIFsentiment is associated with 0.037 higher EFF on day 0, which is 9.5% of the standard deviation of EFF on day 0, and associated with 0.002 higher EFF during the subsequent week, which is 8.8% of the standard deviation of EFF during $t + 1$ to $t + 5$.

In Panel B, the results show that GIFsentiment is negatively correlated with bond fund flows on day 0 and during $t + 1$ to $t + 5$. After including five additional sentiment measures in the regressions, bond fund flows are unrelated to GIFsentiment for day 0 but the relation remains significantly negative for days $t + 1$ to $t + 5$. In terms of the magnitude, a one-standard-deviation higher GIFsentiment is associated with 0.037 lower BFF on day 0, which is 9.3% of the standard deviation of BFF on day 0, and associated with 0.006 lower BFF during the subsequent week, which is 19.8% of the standard deviation of BFF during $t + 1$ to $t + 5$. In summary, high GIFsentiment positively forecasts inflows to equity funds and withdrawal from bond mutual funds in the subsequent week.

TEXTsentiment does not show any association with equity fund flows. While SELFEC shows a flight towards bond mutual funds. Overall, our findings indicate that higher GIFsentiment is associated with a flight away from safety, but not for high TEXTsentiment and high SELFDEC.

4. Conclusion

Observers of financial markets have long argued that investor sentiment (or similar concepts) derives from social interactions between investors. This contrasts with the hypothesis that sentiment effects derive solely from individual-level investor bias in responding to news conveyed by (traditional) mass media. The social interaction hypothesis suggests that to understand investor sentiment, it is important to perform tests that use information about communications between investors. Furthermore, psychological and social media research has emphasized the importance of multimodality in communication—especially, the use of visuals. Among visuals, motion is especially salient and engaging, suggesting that it is useful to perform tests on dynamic visuals.

We propose a novel daily measure of aggregate investor sentiment which we call GIF sentiment. GIF sentiment is based on dynamic visual representations in investing social media discussions. We find that GIF sentiment is correlated with exogenous mood proxies as identified in past literature. Furthermore, we show that GIF sentiment has a positive contemporaneous correlation with the aggregate stock market return, and negatively predicts the market return at horizons of up to one month. GIF sentiment also predicts stock market volatility, retail trading activity, and short selling activity. The return reversal pattern is consistent with transient sentiment-induced mispricing (De Long et al. 1990, Campbell et al. 1993).

These findings are robust to controlling for proxies for sentiment from past literature, including social media proxies such as self-declared sentiment and sentiment derived from the textual valence of postings; Baker-Wurgler sentiment; Michigan Consumer Sentiment; and traditional mass media sentiment. These findings are also robust to controlling for fundamental events measured by daily news-based measure of U.S. economic policy uncertainty and daily U.S. macroeconomic activity index, and past returns.

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

We find sharp differences between results for GIF sentiment and two alternative social media sentiment proxies—one based on text sentiment, the other based on self-declared sentiment, as studied in past literature. We find that GIF sentiment outperforms text sentiment and self-declared sentiment in forecasting aggregate market return reversals. In contrast with the abovementioned negative relation between GIF sentiment and subsequent market returns, text sentiment and self-declared sentiment positively predicts returns in both the short and long run. This sharp contrast probably reflects the fact that dynamic visual representations heavily capture emotion- or attention-driven biases in investor expectations, whereas text and declarations may be more heavily associated with meaningful fundamental information.

Our approach to analyzing dynamic visual content has the advantage of using a large sample of raters within an ecologically relevant investments context. The labeling of GIFs sentiment is directly made by Stocktwits.com participants who are sufficiently interested in the stock market to volunteer their opinions about the stock.

Our analysis of social media sentiment differs from most past studies of social media and the stock market in demonstrating predictability for aggregate market returns rather than individual stocks. In addition, past studies have identified reversals in aggregate market returns at long time horizons of several years (Fama and French 1988, Poterba and Summers 1988). In contrast, GIF sentiment negatively predicts aggregate market returns at daily to weekly time horizons.

To sum up, our study is the first to study GIFs—a key source of dynamic visual representations—as a means of communicating about stock investing. It exploits multimodal communication from dynamic visuals and textual information to construct a high-frequency (daily) market sentiment measure that has predictive power for aggregate stock market returns. As such, this paper contributes to the study of investor sentiment, stock market return predictability, social media in financial markets, and the growing field of social economics and finance.

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Table 1
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 correlations between the sentiment measures. GIFsentiment is calculated following Equation (1) in the text. All variable definitions are in Table A2. The sample period is September 2020 through December 2023.

Panel A: Summary Statistics of Main Variables

Variable	N	Mean	Std Dev	P1	P5	P10	P25	P50	P75	P90	P95	P99
GIFsentiment	838	0.05	0.01	0.00	0.01	0.03	0.03	0.04	0.05	0.06	0.07	0.07
TEXTsentiment	838	0.10	0.02	0.02	0.03	0.05	0.07	0.08	0.10	0.11	0.12	0.12
SELFDEC	838	0.28	0.09	0.00	0.11	0.14	0.17	0.21	0.27	0.35	0.41	0.43
BW	838	0.81	0.77	-0.35	-0.23	-0.06	-0.03	0.97	1.37	2.04	2.07	2.29
ICS (consumer index)	838	68.69	9.65	50.00	51.50	58.20	61.30	67.40	76.80	82.90	84.90	88.30
MEDIAsentiment	838	0.12	0.04	0.00	0.04	0.05	0.07	0.09	0.12	0.14	0.16	0.17
SPX	838	0.04	1.12	-4.32	-3.25	-1.84	-1.30	-0.58	0.05	0.72	1.42	1.84

Panel B: Correlations Between Sentiment Variables

	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
GIFsentiment	1					
TEXTsentiment	0.49	1				
	<.0001					
SELFDEC	0.46	0.13	1			
	<.0001	0.00				
BW	0.47	0.34	0.22	1		
	<.0001	<.0001	<.0001			
ICS	0.16	0.04	0.69	0.02	1	
	<0.0001	0.23	<.0001	0.47		
MEDIAsentiment	0.20	0.12	0.56	0.33	0.46	1
	<.0001	0.00	<.0001	<.0001	<.0001	

Table 2
Relation of GIF Sentiment to Mood Proxies

Panel A reports the results of regressing sentiment measures on mood proxies. GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. 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. DCC is the average daily cloud cover, deseasonalized by each week's average cloud cover. ∆COVID Index is the change in daily containment and closure index. Panel B reports the results of regressing alternative sentiment measures on an information proxy, %PositiveEANews, measured by the percentage of non-negative earnings news on the announcement date. 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. BW and ICS sentiment measures are monthly measures so all variables in BW and ICS regressions are monthly. The other variables and regressions are daily.

Panel A: Pearson Correlation Between Sentiment Measures and Mood Proxies

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
Positive Months	0.171*	-0.876***	0.362***	0.302	0.377	0.154
	(0.083)	(0.000)	(0.000)	(0.545)	(0.500)	(0.136)
Negative Months	-0.811***	-0.531***	-0.022	-0.009	0.069	0.139
	(0.000)	(0.000)	(0.835)	(0.983)	(0.884)	(0.152)
DCC	-0.191*	-0.316***	0.039	-1.52	0.949	-0.185**
	(0.074)	(0.002)	(0.690)	(0.128)	(0.511)	(0.021)
∆COVID Index	-0.779***	-0.245***	-0.526	-0.167***	-0.034	0.073***
	(0.001)	(0.359)	(0.257)	(0.001)	(0.529)	(0.000)
Observations	588	588	588	35	35	588
Adjust R-squared	0.124	0.103	0.024	0.116	0.034	0.137

Panel B: The Relation Between Information Proxy and Three Sentiment Measures

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GIFsentiment	TEXTsentiment	SELFDEC	BW	ICS	MEDIAsentiment
%PositiveEANews	-0.122	-0.411*	0.956***	3.056**	2.054	1.459***
	(-0.632)	(0.051)	(0.000)	(0.043)	(0.172)	(0.000)
Observations	822	822	822	47	47	822
Adjust R-squared	0.001	0.006	0.029	0.001	0.038	0.082

Table 3

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

This table reports the regression estimates of Equation (3) from September 2020 to December 2023. 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	0.230***	-0.186**	-0.975***
	(0.000)	(0.043)	(0.000)
EPU	0.002***	0.003***	0.006***
	(0.000)	(0.006)	(0.003)
ADS	0.064	0.789***	2.212***
	(0.322)	(0.000)	(0.000)
Ret(t)		-0.106	-0.063
		(0.244)	(0.678)
Ret[t - 5,t - 1]	-0.032*	-0.089**	-0.170**
	(0.083)	(0.022)	(0.010)
Ret[t - 21,t - 6]	-0.005	-0.047*	-0.191***
	(0.666)	(0.053)	(0.000)
Log#EA	0.040	0.096*	0.137
	(0.155)	(0.095)	(0.176)
Observations	817	812	797
Adjusted R-squared	0.036	0.049	0.141

Panel B: Six Sentiment Measures

VARIABLES	(1) Ret(t)	(2) Ret[t + 1,t + 5]	(3) Ret[t + 1, t + 20]
GIFsentiment	0.185***	-0.011	-0.707***
	(0.003)	(0.929)	(0.001)
TEXTsentiment	0.241***	-0.057	0.311**
	(0.000)	(0.525)	(0.026)
SELFDEC	0.243***	0.142	0.577**
	(0.002)	(0.323)	(0.030)
BW	-0.430***	-0.417***	-1.374***
	(0.000)	(0.000)	(0.000)
ICS	-0.353***	-0.041	0.238
	(0.000)	(0.738)	(0.354)
MEDIAsentiment	0.383***	-0.028	-0.215
	(0.000)	(0.791)	(0.261)
EPU	0.001**	0.003**	0.004*
	(0.018)	(0.031)	(0.065)
ADS	0.058	0.867***	2.158***
	(0.360)	(0.000)	(0.000)
Ret(t)		-0.155*	-0.249
		(0.095)	(0.112)
Ret[t - 5,t - 1]	-0.069***	-0.131***	-0.313***
	(0.000)	(0.001)	(0.000)
Ret[t - 21,t - 6]	-0.041***	-0.075***	-0.288***
	(0.000)	(0.003)	(0.000)
Log#EA	0.121***	0.142**	0.253**
	(0.000)	(0.017)	(0.011)
Observations	817	812	797
Adjusted R-squared	0.205	0.0660	0.217

Table 4

GIF sentiment, Text sentiment, SELFDEC and Limits to Arbitrage

This table reports the regression estimates of Equation (3) from September 2020 to December 2023. 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	0.453***	-0.268	-1.928***	0.245***	-0.213**	-1.077***
	(0.000)	(0.271)	(0.000)	(0.000)	(0.023)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.046	0.027	0.088	0.0387	0.049	0.147
(Small-Large) p-values	0.0026	0.6880	0.1015			

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	0.331***	-0.212	-2.313***	0.190***	-0.028	-0.765***
	(0.002)	(0.446)	(0.000)	(0.002)	(0.831)	(0.001)
TEXTsentiment	0.277***	-0.531**	-2.027***	0.259***	-0.056	0.343**
	(0.000)	(0.046)	(0.000)	(0.000)	(0.543)	(0.016)
SELFDEC	0.570***	0.952**	3.503***	0.283***	0.181	0.690**
	(0.000)	(0.022)	(0.000)	(0.001)	(0.228)	(0.012)
BW	-0.648***	-0.836***	-2.422***	-0.468***	-0.479***	-1.577***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ICS	-0.541***	-0.339	0.117	-0.381***	-0.060	0.190
	(0.000)	(0.231)	(0.803)	(0.000)	(0.638)	(0.464)
MEDIAsentiment	0.406***	0.247	0.665	0.392***	-0.013	-0.219
	(0.000)	(0.272)	(0.159)	(0.000)	(0.907)	(0.260)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.131	0.052	0.202	0.222	0.070	0.236
(Small-Large) p-values	0.1761	0.5559	0.0046			

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	0.602***	-0.664***	-3.814***	0.134***	-0.205***	-1.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.088	0.058	0.179	0.031	0.042	0.155
(High-Low) p-values	0.0000	0.0739	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	0.275***	-0.423	-4.552***	0.097**	-0.113	-0.991***
	(0.007)	(0.129)	(0.000)	(0.012)	(0.177)	(0.000)
TEXTsentiment	0.347***	-1.183***	-2.927***	0.138***	-0.106*	-0.027
	(0.000)	(0.000)	(0.000)	(0.000)	(0.063)	(0.765)
SELFDEC	1.263***	0.623	3.028***	0.167***	0.104	0.598***
	(0.000)	(0.158)	(0.000)	(0.001)	(0.269)	(0.001)
BW	-0.960***	-0.465**	-0.756	-0.277***	-0.239***	-0.819***
	(0.000)	(0.049)	(0.151)	(0.000)	(0.001)	(0.000)
ICS	-0.980***	-0.068	1.280**	-0.214***	0.036	0.293*
	(0.000)	(0.829)	(0.046)	(0.000)	(0.656)	(0.077)
MEDIAsentiment	0.517***	0.280	-0.124	0.241***	-0.022	-0.146
	(0.000)	(0.197)	(0.785)	(0.000)	(0.759)	(0.250)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.309	0.104	0.290	0.210	0.0629	0.242
(High-Low) p-values	0.0000	0.2145	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	0.647***	-0.399*	-3.099***	0.034***	-0.100***	-0.687***
	(0.000)	(0.063)	(0.000)	(0.001)	(0.004)	(0.000)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.081	0.053	0.151	0.081	0.128	0.217
(HighVol-LowVol) p-values	0.0000	0.2836	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	0.340***	-0.297	-4.425***	0.017	-0.013	-0.620***
	(0.003)	(0.306)	(0.000)	(0.285)	(0.803)	(0.000)
TEXTsentiment	0.298***	-1.281***	-3.554***	0.043***	-0.085***	0.024
	(0.001)	(0.000)	(0.000)	(0.000)	(0.006)	(0.708)
SELFDEC	1.195***	0.990**	4.163***	0.055***	-0.096*	-0.012
	(0.000)	(0.016)	(0.000)	(0.008)	(0.099)	(0.925)
BW	-0.906***	-0.473**	-0.323	-0.073***	-0.043	-0.334***
	(0.000)	(0.039)	(0.525)	(0.000)	(0.235)	(0.000)
ICS	-0.905***	-0.069	1.504**	-0.051***	0.094**	0.410***
	(0.000)	(0.804)	(0.012)	(0.000)	(0.017)	(0.000)
MEDIAsentiment	0.600***	0.348	-0.082	0.052***	0.007	-0.018
	(0.000)	(0.124)	(0.862)	(0.000)	(0.841)	(0.835)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	812	797	817	812	797
Adjusted R-squared	0.279	0.114	0.312	0.137	0.139	0.267
(HighVol-LowVol) p-values	0.0023	0.3565	0.0000			

Table 5

Regressions of Stock Market Volatility on the Sentiment Proxies

This table reports the regression estimates of Equation (4) from September 2020 to December 2023. 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](%)	(1) Volatility[t,t + 5](%)
|GIFsentiment|	0.056**	0.084***
	(0.038)	(0.008)
|TEXTsentiment|		-0.062***
		(0.000)
|SELFDEC|		-0.099***
		(0.007)
|BW|		-0.138***
		(0.000)
|ICS|		-0.014***
		(0.000)
|MEDIAsentiment|		-0.013
		(0.591)
EPU	0.001***	0.001***
	(0.002)	(0.001)
ADS	-0.012	-0.035
	(0.658)	(0.202)
Ret[t - 5,t - 1]	-0.061***	-0.064***
	(0.000)	(0.000)
Ret[t - 21,t - 6]	-0.026***	-0.029***
	(0.000)	(0.000)
VOL[t - 5,t - 1]	0.224***	0.187***
	(0.000)	(0.000)
Log#EA	0.048***	0.045***
	(0.000)	(0.000)
Observations	817	817
Adjusted R-Squared	0.403	0.418

Table 6

Regression of Trading Outcomes on the Sentiment Proxies

This table reports the regression estimates of Equation (5) for total trading volume in Panel A, using data from September 2020 to December 2023. In Panel B, we report the regression estimates of Equation (6) from September 2020 to April 2023 for short sales volume. For the dependent variables, LogTotalVol is the natural logarithm of one plus total daily trading volume, calculated using alternative windows. LogShortVolume is the natural logarithm of one plus daily short sale volume, calculated using alternative windows. The main independent variable, GIFsentiment is the daily appearance-weighted average sentiment of GIFs posted on Stocktwits. 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: Total Trading Volume

VARIABLES	(1) LogTotalVol(t)	(2) LogTotalVol [t + 1, t + 5]	(3) LogTotalVol(t) [t + 1,t + 20]	(4) LogTotalVol(t)	(5) LogTotalVol [t + 1, t + 5]	(6) LogTotalVol(t) [t + 1,t + 20]
|GIFsentiment|	0.048***	0.017**	0.009	0.029**	-0.004	0.017*
	(0.000)	(0.030)	(0.401)	(0.034)	(0.644)	(0.079)
|TEXTsentiment|				0.012	-0.000	0.013
				(0.298)	(0.970)	(0.128)
|SELFDEC|				0.030	0.028***	-0.006
				(0.103)	(0.008)	(0.628)
|BW|				0.039*	0.045***	0.048***
				(0.056)	(0.000)	(0.002)
|ICS|				0.026	0.012	0.015
				(0.142)	(0.241)	(0.292)
|MEDIAsentiment|				0.033***	0.026***	0.017**
				(0.001)	(0.000)	(0.048)
Controls	YES	YES	YES	YES	YES	YES
Observations	817	817	817	817	817	817
Adjusted R-squared	0.792	0.897	0.758	0.837	0.921	0.831

Panel B: Short Sale Volume

VARIABLES	(1) LogShortVolume(t)	(2) LogShortVolume [t + 1,t + 5]	(3) LogShortVolume [t + 1,t + 20]	(4) LogShortVolume(t)	(5) LogShortVolume [t + 1,t + 5]	(6) LogShortVolume [t + 1,t + 20]
GIFsentiment	0.034**	0.046***	0.037***	-0.013	0.019	0.029*
	(0.033)	(0.001)	(0.000)	(0.627)	(0.417)	(0.052)
TEXTsentiment				-0.077***	-0.101***	-0.057***
				(0.000)	(0.000)	(0.000)
SELFDEC				0.005	-0.003	-0.001
				(0.862)	(0.928)	(0.949)
BW				0.081***	0.053***	0.015
				(0.000)	(0.002)	(0.215)
ICS				0.067***	0.052***	0.025**
				(0.000)	(0.001)	(0.018)
MEDIAsentiment				-0.062***	-0.057***	-0.016*
				(0.000)	(0.000)	(0.094)
Controls	YES	YES	YES	YES	YES	YES
Observations	635	635	635	635	635	635
Adjusted R-squared	0.574	0.587	0.753	0.565	0.575	0.755

Table 7

Regression of Equity and Bond Fund Flows on the Sentiment Proxies

This table reports the regression estimates of Equation (8) 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

VARIABLES	(1) EFF(t)	(2) EFF[t+1, t + 5]	(3) EFF(t)	(5) 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

VARIABLES	(1) BFF(t)	(2) BFF[t+1, t + 5]	(3) BFF(t)	(5) 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,

from September 1, 2020 to December 31, 2023

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	-0.971	xTiTnkt1IjaaTWoPny	0.997
kfd19XS70QrTQmsw7k	-0.952	2cpPfXUit2JSU	0.995
UfX4XeBMXWmNoGvBVK	-0.858	PnahEQ7Ify1JvhQrag	0.991
m6tNZJt9cG3ss	-0.819	YpwSw00aOaoIhPVSAF	0.977
NUZ5OqHdbknHa	-0.805	f9AxU1ieQdqfHbbf13	0.977
IQ9KefLJHfJPq	-0.797	XZVYAstOMLUDndgFPS	0.965
xA5oN4RDaCneQfcC8x	-0.795	3o6wNKjI7XkipBHUjK	0.950
w4NAKAenurl8k	-0.775	RETg1tippXtNm	0.947
utMwbVuNZSSlvej2En	-0.774	6xE1FNcorRInS	0.945
9gGi02YPpLo2ueSxvh	-0.772	TcdpZwYDPlWXC	0.943
JpN6nbJqz5l3mbMnod	-0.768	3o7TKSlLGOXZGOfmes	0.941
l0K4puBUN4w6G4ksE	-0.747	ULoie47jnvxwtkx90t	0.941
jqfel7Z3XwTHCl26nT	-0.742	t6QjP9pcOlFDO	0.938
dvZSDOywoCM4Sro65Q	-0.721	T9YdDlG5gHj6U	0.936
9detkWt4jBdhVm0UCk	-0.718	QMyF0t2nkwNNt2sJp2	0.933
y31rRE5h3wyPXey8vx	-0.702	9z8Jpk8Sl9QRrWqXlR	0.931
C5ZIna5oroan9cdHz9	-0.700	VF6zQwFDlpE12FzBUB	0.930
LkuPxRS0F6gmc	-0.691	2UvFRCjSFuk1iz1Rmb	0.929
ckEwMluJd0WnFXPOYC	-0.681	YbHnru6KfNiUGeNeCf	0.928
fXeRGki5DiU5G	-0.667	9rjzS2QYAk1paKD7uk	0.926
11Y9TiZzmEBe25QRSw	-0.658	3xz2BzSNxkwPqF8Wdy	0.926
zzQKrTT326GZG2s8O9	-0.658	1eujMV2UTtuMbncu5T	0.926
9l84gf0TK6B7C3UCZp	-0.657	ixYRj3H9HOzWE	0.925
11ITiHSwbGTXmU	-0.656	EQZD8MDEopRBlSgQL7	0.924
MEeF0LoWyiaJnqFXol	-0.648	m9523AAgxz9Lj7ZMau	0.921

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
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
VWRETD (%)	Daily CRSP value-weighted return.	CRSP
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
DIA (%)	Daily return of SPDR Dow Jones Industrial Average ETF.	CRSP
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
IWB (%)	Daily return of Russell 1000 Index ETF.	CRSP
IWM (%)	Daily return of Russell 2000 Index ETF.	CRSP
INDU (%)	Daily return of Dow Jones Industrial Average Index.	CRSP
Log#EA	Daily natural logarithm of one plus the number of earnings announcements.	COMPUSTAT
QQQQ (%)	Daily return of PowerShares QQQ Trust.	CRSP
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 (%)	Daily return of SPDR S&P 500 ETF.	CRSP
Text sentiment	Daily average sentiment of text in all postings, standardized to have a zero mean and unit variance.	Stocktwits