Sentiment about Others

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Abstract

Applying large language models to more than 46 million StockTwits posts, we distinguish messages expressing investors' own outlook from those describing others' expected actions and extract sentiment associated with these posts. This yields firm-week measures of own and subjective sentiment. We find that references to others are pervasive and typically more optimistic than investors' own views. Retail order imbalance increases with own sentiment but decreases with subjective sentiment, indicating contrarian trading against beliefs about others. Subjective sentiment also positively predicts short-horizon returns, especially where contrarian retail trading is strongest, consistent with contrarian liquidity provision slowing price adjustment and generating return continuation.

JEL: C55, C80, D84, G11, G41

Keywords: higher order beliefs, sentiment, disagreement, retail trading, text analysis, LLM.

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I. Introduction

Beliefs play a central role in financial decision-making. In many settings, investors rarely act solely on their own assessments of the future outlook. Rather, they continually evaluate how other market participants interpret information, how they react to news, and how they might trade in response. These beliefs about others, that is, higher order beliefs (HOB), shape how narratives form, how information travels, and how strategic behavior unfolds.

Classic theories in finance emphasize that beliefs about others are central to price formation, learning, beauty contests, and speculative trading. Yet, despite the importance of higher order reasoning, direct empirical evidence on how investors perceive the beliefs of others remains scarce. In this project, we fill this gap by constructing a new large-scale measure of higher order sentiment and using it to study how investors describe others' views, how they perceive others' sentiment, and how these perceptions relate to market outcomes. In particular, we apply modern large language models (LLMs) to more than 46 million StockTwits posts to determine whether a message reflects the author's own view or describes their expected actions of other investors.

Traditional lexicon-based sentiment tools cannot make this distinction because they capture polarity but not whether the sentiment targets the author or others, and they do not reliably identify relational statements. Using language models allows us to detect references to others directly in the text and separate first order beliefs from higher order beliefs at scale. With this distinction in hand, we can examine how discussions about others change with market conditions and how perceptions of others' sentiment relate to disagreement, valuation ratios, returns, and retail trading activity.

We first classify each StockTwits message as either expressing the author's own outlook or describing the reasoning or expected actions of other investors. Messages referencing others yield our initial selection of higher-order messages. However, references to others can take different temporal forms: investors may rationalize others' past behavior, comment on others' current reactions, or speculate about what others are likely to do in the future. Because higher-order beliefs are conceptually about expectations of others' future beliefs or actions, we further classify higher-order messages by their temporal orientation

and focus our analysis on those that explicitly refer to others' future expectations, excluding messages that merely rationalize past outcomes or describe contemporaneous conditions.

For each higher-order message, we also extract the sentiment that the writer attributes to others, which provides a measure of *subjective sentiment*. By contrast, StockTwits allows users to explicitly label each post as *bullish* or *bearish* at the time of posting, and we use these self-reported tags as a direct measure of the author's *own sentiment*.

The data reveal several notable patterns in how investors communicate higher order beliefs. References to others' reasoning are common: roughly one third of messages describe what other traders think or are expected to do, and this share remains stable over time. Although higher order and first order posts use similar vocabularies, reflecting that both focus on underlying market outcomes, HOB messages more often contain terms that point to groups of investors such as people, shorts, or retail. Investors also assign systematically different sentiment to others than to themselves. Subjective sentiment is consistently more pessimistic than own sentiment, and the gap widens during periods of market stress. These facts indicate that higher order communication is a regular part of investor dialogue and conveys information not captured by first order beliefs.

Higher order posting varies with investors' own beliefs and the information environment. Investors talk more about others when they are optimistic themselves but view others as more pessimistic, suggesting that differences between one's own views and the views ascribed to others prompt more discussion about others' reasoning. Higher order posting also increases when market signals diverge, specifically, when returns are weak but valuation ratios are high. In these situations, when prices and fundamentals move in different directions, investors appear to pay closer attention to how others interpret the same information. Overall, higher order communication rises both when investors sense a gap between their own beliefs and those they attribute to others and when markets send conflicting signals.

Perceptions of others' sentiment also change with market conditions. Subjective sentiment moves with investors' own views but is more pessimistic on average, especially when disagreement across investors is higher or when idiosyncratic volatility is elevated. This suggests that in noisier settings, investors assume others hold more cautious beliefs. Subjective sentiment also becomes more responsive to return movements when valuation ratios are high, indicating that the beliefs investors attribute to others depend jointly on prices and their alignment with fundamentals. Together, these results show that perceptions of others' expectations depend not only on one's own beliefs but also on the broader informational environment.

A common concern in using textual data from news or social media is that these sources may not represent the beliefs of the average investor. Previous work shows that sentiment extracted from newspaper coverage predicts returns and trading activity (Tetlock, 2007; Tetlock, Saar-Tsechansky, and Macskassy, 2008). More recent studies using investor social networks reach similar conclusions: posts on platforms such as StockTwits can capture economically meaningful belief heterogeneity and attention that is reflected in trading activity and price dynamics (Cookson and Niessner, 2020; Cookson, Lu, Mullins, and Niessner, 2024).

We next examine retail order flow to assess how our sentiment measures relate to actual trading behavior. Retail buying increases with investors' own stated outlook, consistent with the idea that retail traders add to positions when they are personally optimistic. Retail order imbalance also rises with disagreement (the dispersion in first order beliefs within a firm-week), consistent with evidence in Cookson and Niessner (2020) that disagreement tends to accompany higher trading activity. After controlling for own sentiment, trading patterns display a contrarian response to beliefs about others: retail investors buy slightly more when they perceive others as more pessimistic. This matches the pattern emphasized in Gorodnichenko and Yin (2025), where investors lean against the sentiment they attribute to others when they see it as excessive or sentiment-driven rather than informational. Average magnitudes are statistically significant but, nonetheless, small

in magnitude: a one-standard-deviation increase in subjective sentiment shifts retail order imbalance by about 0.012 standard deviations.

While the average relationship between beliefs about others and trading is economically modest, these mean effects mask substantial heterogeneity across stock characteristics. In particular, we find that the association between retail order imbalance and subjective sentiment becomes an order of magnitude larger when retail activities are more active, when uncertainty is high, or when the stocks get more illiquid: in these environments, the same increase in relative sentiment is associated with a around 0.10-standard-deviation reduction in retail net buying. These patterns suggest that investors' contrarian trading behaviors are not uniform, but instead depends on the broader market environment.

We then turn to the implications of sentiment about others for return dynamics. Here, subjective and own sentiments display sharply different predictive patterns. First, both subjective sentiment and own sentiment are associated with significant contemporaneous return. Meanwhile, consistent with the literature documenting investor optimism forecasts subsequent reversals (Baker and Wurgler, 2006; Tetlock, 2007), investors' own optimism predicts short-horizon reversals: a one-standard deviation increase in own sentiment predicts a 4.1% lower annualized return in the following week. In contrast, subjective sentiment positively predicts future returns. A one-standard deviation increase in subjective sentiment predicts a 5.5% higher return in the next week and an 11.9% higher cumulative return over the subsequent three weeks. This predictability is stronger for stocks with high retail trading intensity, elevated uncertainty, and low liquidity, mirroring the settings in which contrarian retail trading is most pronounced.

Taken together, our results align with Laarits and Sammon (2025) and Luo et al. (2025) in suggesting a state-dependent role for retail trading. When contemporaneous returns are high, investors become more optimistic about future outcomes but simultaneously perceive others as overly optimistic. Conditioning on this assessment, they reduce net buying against upward price pressure when they perceive others as more optimistic. This contrarian retail trading does not lead to immediate price reductions; rather,

it appears to slow the incorporation of favorable information into prices, allowing returns to continue drifting in the short run, especially among stocks with higher retail participation, lower liquidity, and weaker institutional trading presence.

This paper contributes to the vast literature on higher order beliefs in financial markets by providing the first large scale, high-frequency empirical measure of beliefs about others. Theoretical work identifies several mechanisms through which beliefs about others influence prices and trading. In beauty-contest and strategic-complementarity models (Allen et al. 2006; Bacchetta and van Wincoop 2006, 2008; Nimark 2017), investors care about others' expectations because others' actions amplify or mediate the effect of information. In social-learning and cascade models (Bikhchandani, Hirshleifer, and Welch 1992; Avery and Zemsky 1998; Alevy et al. 2007), investors reason about how others interpret public and private signals. In difference-of-opinion and speculative-trading models (Harrison and Kreps 1978; Harris and Raviv 1993; Kandel and Pearson 1995; Scheinkman and Xiong 2003; Banerjee and Kremer 2010), awareness of others' heterogeneous valuations drives trade and volatility.

Empirically, Egan et al. (2014) and Schmidt-Engelbertz and Vasudevan (2025) show that individual investors often trade in speculative ways, and Gorodnichenko and Yin (2025) document contrarian responses to beliefs about others using randomized belief variation. We extend this work by constructing a firm-level, high-frequency measure of higher order sentiment across a large panel of stocks, allowing us to study how perceived beliefs evolve over time and how they relate to retail order imbalance under different conditions.

Our analysis also contributes to the literature on disagreement in financial markets. Prior theoretical and empirical studies show that heterogeneous beliefs can generate trade and affect prices (Miller 1977; Harris and Raviv 1993; Kandel and Pearson 1995; Scheinkman and Xiong 2003; Banerjee and Kremer 2010; Diether, Malloy, and Scherbina 2002; Boehme, Danielson, and Sorescu 2006; Yu 2011; Da, Engelberg, and Gao 2015). But these measures capture disagreement in the cross-section and cannot show how much investors think others disagree. We contribute by constructing a firm-level, high-frequency

measure of subjective disagreement, which is the difference between own sentiment and subjective perception of the sentiment of others, providing a new dimension of belief heterogeneity that can be linked to trading behavior in real time.

Our work also contributes to the growing literature that uses text as data in economics and finance. Recent research applies topic models and machine learning methods to extract information from news and other texts (Hansen et al. 2018; Larsen and Thorsrud 2019; Thorsrud 2020; Ellingsen et al. 2020; Chahrour et al. 2021; Baker et al. 2016, 2021). In finance, machine learning approaches have been used to forecast returns and macroeconomic variables from raw text (García 2013; Manela and Moreira 2017; Ke, Kelly, and Xiu 2019; Kelly, Manela, and Moreira 2021). These methods, however, treat text as bags of words and are not designed to detect relational content. We show that large language models can identify how investors describe the reasoning, expectations, or sentiment of others, a form of communication that traditional word-count and topic-model approaches cannot reliably capture. This expands text-as-data tools to a new dimension of investor communication and links sentiments about others to firm-level trading behavior in real time.

The remainder of this paper is organized as follows: Section II describe the data. Section III discuss the subjective sentiment measurement. Section IV studies the fraction of HOB posts and subjective sentiment. Section V document the relationship between subjective sentiment of trading activities and return dynamics. Section VI concludes the paper.

II. Data

A. StockTwits

Launched in 2008, StockTwits is a prominent online social media platform dedicated to investor communication and information sharing. The platform enables users to post concise, Twitter-like messages, utilizing "cashtags" (e.g., $SPY) to directly link discussions to specific stock, ETF or crypto. Over the years, StockTwits has evolved into one of the most widely used platforms for the real-time exchange of market sentiment and

investment ideas. Recent web-traffic metrics confirm its ongoing prominence: as of July 2025, StockTwits ranked approximately 760th among U.S. websites, with around 18.2 million monthly visits. Its user base is disproportionately male and more likely to hold advanced educational degrees relative to typical internet demographics, underscoring its appeal to a comparatively sophisticated retail investor audience.

Our dataset is obtained directly from StockTwits, covering the period from January 2014 to July 2024. The dataset contains about 301,082,004 unique messages posted from 1,598,577 distinct users. For each post, we observe the textual content of message, post timestamp, as well as the user identifier. A distinctive feature of StockTwits is that it allows users to self-disclose their sentiment by explicitly labeling each message as either "Bullish" or "Bearish".

We restrict our sample following the procedures in Cookson and Niessner (2020) and Cookson et al. (2024). Specifically, we retain only messages that are linked to a publicly traded U.S. firm, contain a self-reported sentiment indicator, and have a minimum length of ten words after removing emojis and URL links. After applying these filters, the sample retains 46,902,172 messages associated with 12,374 unique firms. Figure 1 shows the weekly number of posts during our sample. The number of posts every week is relatively stable at around 10,000 prior to 2016. Starting in 2017, activity rises to roughly 50,000 posts per week, with a further surge to about 100,000 posts during 2020 to 2022.

B. Other Datasets

We link the StockTwits sample with stock information from CRSP. We focus on common stock in the U.S. listed on NYSE, AMEX and NASDAQ. We then merge the data with accounting information from COMPUSTAT and analyst forecast information from I/B/E/S.

To measure retail trading activities, we obtain retail flow data from Alpha Signals Retail Flow Database from S&P Global. This database provides daily volumes and shares on retail purchase, sell, and short for each stock from 2016 to 2025. The data is sourced from market makers and represent actual trades transacted by retail traders. Overall, the data is expected to cover more than 80% of total retail trading activity.

III. Methodology

Traditional lexicon-based natural language processing techniques are designed to detect the presence of specific words or phrases. While effective for tasks where meaning is tied to identifiable tokens (e.g., sentiment classification), these methods perform poorly when the relevant information is relational rather than lexical, such as statements comparing agents, inferring motives, or describing how one group responds to another. Such statements are typically conveyed through context, syntax, or implicit references rather than fixed vocabulary, which often rely on pragmatic cues including implication, sarcasm, references to collective behaviors. Therefore, the effective interpretation requires how language is used, not just which words appear.

Because the information we seek is inherently relational, which requires interpretation of how writers describe other agents' actions, expectations, or reactions, lexicon-based methods are insufficient. LLM, by contrast, can parse contextual meaning, infer implied relationships, and interpret nuanced references. This makes them especially well-suited for our application.

A. Classifying HOB Posts

We employ Gemini 2.0 Flash to analyze each post and detect whether the message discusses HOB. Our approach involves two steps. In the first step, we use Gemini 2.0 Flash to classify whether a message directly or indirectly references others' beliefs, or does not mention others' beliefs at all, based on the following prompt:

> *You are a textual analysis expert specialized in identifying Higher-Order Beliefs (HOB) in stock market discussions.*
>
> *A Higher-Order Belief (HOB) occurs when an individual discusses their perceptions of other people's (or the market's, or a collective "they") expectations, beliefs, or reactions regarding a stock, the market, or a financial event. This is distinct from the author's own direct, personal opinion or prediction about the stock or market.*
>
> *Important Criterion:*

Classify a post based on whether it explicitly states or strongly implies beliefs, expectations, or reactions attributed to others.

Classification Scale & Definitions:

*0 (No HOB): The post expresses *only* the author's personal belief, opinion, prediction, action, or a factual statement. There is no mention, explicit or implicit, of what other individuals, groups, or the market collectively believe, expect, or how they are reacting.*

*1 (Indirect/Implicit HOB): The post *indirectly suggests, implies, or questions* what others (e.g., "the market," "sentiment," "chatter," "some people," "they") might be thinking, believing, or expecting. The reference is not a direct attribution of a specific belief to a specific group but points towards a collective mood, assumption, or a general sense of others' views. It might also be a question about what others believe.*

*2 (Direct/Explicit HOB): The post *directly and explicitly states or quotes* what specific other individuals, named groups (e.g., "traders," "analysts," "retail investors," "shorts," "everyone on this board"), or collective entities (e.g., "Wall Street," "the consensus") believe, expect, are thinking, or how they are reacting.*

We define a message as a HOB message if Gemini classifies as either a direct or indirect reference to others' beliefs.

An important preliminary step is to ensure that an LLM possesses a coherent and conceptually consistent understanding of higher-order belief. To gauge this, we directly query Gemini and examine how it characterizes the notion of HOB using the following prompt:

You are a textual analysis expert specializing in social network communication, particularly within financial contexts like StockTwits.

First, based on your knowledge and expertise in analyzing financial social media:

1. Please provide your comprehensive definition of a "higher-order belief" (HOB) as it applies to discussions about stocks or financial markets

If Gemini encodes a conventional understanding, we would expect its answers to accord with widely accepted descriptions. The Gemini response we get is

In the realm of financial discussions, a higher-order belief (HOB) refers to a belief about someone else's belief regarding a particular stock, market trend, or economic event. It's not simply stating your own opinion (a first-order belief), but rather speculating, inferring, or explicitly stating what another person or group of people believes. The "order" refers to the level of nesting of beliefs.

First-order belief: "I think Tesla will go up." (My direct opinion)

*Second-order belief: "I think *John* thinks Tesla will go up." (My belief about John's belief)*

*Third-order belief: "I think *John* thinks *Mary* thinks Tesla will go up." (My belief about John's belief about Mary's belief)*

Overall, Gemini 2.0 Flash appears to have a coherent understanding of the concept of higher-order beliefs. After this step, 17,941,612 messages are assigned as HOB posts. That is around 38% of the messages are classified as representing other's motives.

B. Expectations vs Rationalizations

When investors refer to the beliefs or actions of others, they need not always concern expectations about future behavior. Such statements may instead rationalize past price movements or describe contemporaneous market reactions. Because higher-order beliefs are conceptually about expectations of others' future beliefs or actions, it is important to distinguish forward-looking references from those that reflect retrospective or contemporaneous commentary.

To isolate higher-order beliefs that refer to future expectations, we further classify each HOB message according to whether it refers to past events, current conditions, or future beliefs. We use Gemini 2.0 Flash to assign each HOB message to one of three categories: "Past," "Present," or "Future", and focus our analysis on messages that explicitly describe others' future beliefs or actions. Specifically, we use the following prompt to classify the temporal orientation of HOB messages:

Task 1: HOB Time Analysis: Identify whether the higher-order-belief refers to:

0 = Past (other's beliefs or actions in the past)

1 = Present (other's current beliefs, opinions or reactions)

2 = Future (other's expected future beliefs or reactions)

We also measure a degree of uncertainty associated with investors' higher-order statements by assigning an uncertainty score to each HOB message, capturing how clearly the investor articulates beliefs about others' beliefs. The prompt we use to assign the uncertainty score is

> *Task2: Uncertainty score: assign an uncertainty score between 0 and 1. This uncertainty should be inferred directly from how clear or ambiguous the higher-order-belief sentiment is.*

We analyze the 17,941,612 Gemini-classified HOB message using these prompts and classify each HOB message to whether they refer to "Past", "Present" or "Future". We find that 5,826,069 messages express beliefs or opinions about other's future expectation, 7,179,330 messages discuss current reactions, and 4,936,213 messages describe past event, accounting for approximately 32.5%, 40%, and 27.5% of the HOB messages, respectively. Motivated by this distribution, we subsequently redefine expectation-forming HOB messages as those that explicitly describe other's future beliefs, which more closely align with conceptual definition of higher-order-belief. Overall, StockTwtis messages that express beliefs about other's future expectation represent about 12.59% of total messages in our sample.

C. Measuring Sentiments

We next use Gemini to extract a sentiment score from each message that contains a higher-order belief. The sentiment evaluation refers exclusively to the tone of the belief attributed to others, not to the poster's own first-order view. We use the following prompt to measure the sentiment for each HOB message

> *Sentiment Analysis: Assign a sentiment score based on the tone of the HOB (not the first-order belief). Ranges from -1 to 1, where 1 means extremely positive and -1 means extremely negative, 0 means neutral.*

We construct *Subjective Sentiment* defined as the sentiment score of the HOB messages generated by Gemini. By contrast, StockTwits users often post messages with a self-assigned sentiment tag that can be either "bullish" or "bearish". Following Cookson and

Niessner (2020), we use these tags to represent the user's own belief about the asset outlook. We, therefore, define *Own Sentiment* as a measure coded to one if the post has a tag of "bullish" and minus one if "bearish". To ensure meaningful variation in disagreement, we exclude firm-week observations with fewer than three posts. For each remaining firm-week, we compute the average *Subjective Sentiment* and the average *Own Sentiment.* To ensure that our analysis focus on the same sample, we remove observations with no HOB messages. The resulting panel contains 210,645 firm-week observations, covering a total of 4,315 unique firm over 551 weeks from January 2014 to July 2024. Each week, there are roughly 381 firms.[1]

D. Some Basic Patterns

We begin by documenting the linguistic and qualitative features that distinguish higher-order-belief (HOB) posts from first-order-belief (FOB) posts. Figure 2 presents word clouds constructed from FOB messages, HOB messages, and the difference between the two. Three observations stand out. First, Panels A and B show that the most frequent words in both FOB and HOB posts are trading-related terms such as *will*, *buy*, *shares*, *now*, and *going*. These overlaps indicate that both types of posts revolve around the same underlying investment themes, such as predicting price movements, describing trading actions, and interpreting market conditions. Second, the broad similarity of the two clouds confirms that HOB and FOB messages do not rely on distinct vocabularies. This is expected as both often reflect beliefs about future market outcomes. This also illustrates why traditional lexicon-based NLP methods are insufficient for identifying higher-order content: because FOB and HOB posts use nearly identical vocabularies, distinguishing them requires contextual language understanding rather than simple word counts. Third, Panel C isolates words that appear disproportionately in HOB posts relative to FOB posts. Terms such as *people*, *bears*, *shorts*, *think*, *everyone*, and *retail* explicitly reference other investors or groups, matching the conceptual definition of higher-order beliefs. In the end, Panel D plots the words that disproportionally appear more in the posts that refer to the future instead of current of past.

[1] Online Appendix Figure A.1 plots the ratio of total market capitalization of the firms in our sample to that in CRSP, which shows that the final sample covers around 75% of total market capitalization.

This word cloud includes more words that refer to actions in the future, include *will*, *going*, and *soon.* Figure 3 provides further confirmation using concrete examples: FOB posts express the user's own outlook, whereas HOB posts explicitly describe what other traders believe or are expected to do.

We next document the frequency and distribution of HOB posts. Figure 4 presents the share of HOB messages in our sample. Panel A plots the weekly time-series evolution of the cross-firm average fraction of HOB posts, while Panel B reports the distribution of firm-level means. The overall share of HOB messages is remarkably stable at roughly 35% throughout the sample, indicating that the propensity to reference others' beliefs does not fluctuate significantly with market conditions. However, this stable aggregate pattern masks considerable cross-sectional heterogeneity. Panel B shows that while many firms have moderate levels of HOB activity, others have consistently higher or lower fractions, underscoring meaningful differences in how much investors discuss others' beliefs across firms.

Finally, Figure 5 the evolution of subjective and own sentiment. Panel A shows that both measures are predominantly positive over the sample period, though subjective sentiment capturing the tone investors attribute to others is consistently higher than own sentiment. This indicates that investors tend to portray others as more optimistic than themselves. Both sentiment series exhibit substantial time-series variation, suggesting that neither first-order nor higher-order beliefs remain anchored around a fixed level. Panel B plots relative sentiment, defined as the difference between standardized subjective and own sentiment. Relative sentiment fluctuates widely across the sample. For example, during the onset of COVID, subjective sentiment fell much more sharply than own sentiment, indicating that investors perceived others as especially pessimistic early in the pandemic. During the rebound in late 2020, subjective sentiment rose more quickly than own sentiment, suggesting that investors viewed others as becoming unusually optimistic relative to their own stated beliefs.

To benchmark our sentiment measures against an established survey-based approach to investor beliefs, we compare them with Robert Shiller's Investor Confidence

Surveys (Shiller, 2000). These data have been widely used to study investors' expectations and trading motives, including recent work on speculative trading (Schmidt-Engelbertz and Vasudevan, 2025) and the term structure of return expectations (Bastianello and Peng, 2025). While the elicitation environment and respondent population differ substantially from those in our setting, the Shiller surveys provide a useful point of comparison for assessing whether our sentiment measures capture related belief components.

We measure subjective sentiment as the monthly average of the difference between the answers to questions F. (11) and G. (12):

> *F. (11) Many people are showing a great deal of excitement and optimism about the prospects for the stock market in the United States, and I must be careful not to be influenced by them*
>
> *True. 2. False. 3. No opinion*
>
> *G. (12) Many people are showing a great deal of pessimism about the prospects for the stock market in the United States, and I must be careful not to be influenced by them*
>
> *True. 2. False. 3. No opinion*

Following Engelbertz and Vasudevan (2023), we encode all answers of True/Buy with 1, False/Sell with -1, and No opinion/Hold with 0. We then measure own sentiment as the monthly average of the answers to question C. (4):

> *C. (4) How much of a change in percentage terms do you expect [for the Dow Jones index] in the following 1 month?*

Since the measures in the investor confidence survey and in our setting have different scales, we similarly construct a measure of relative sentiment as the standardized residuals from regressing subjective sentiment on own sentiment.

Figure 6 plots the relative sentiment measure constructed from the Shiller survey against our corresponding measure. Given differences in question framing, temporal aggregation, and the underlying investor samples, a tight correspondence between the two series is not expected. Nonetheless, we find a statistically significant, albeit modest, positive relationship between the measures. In particular, a one-standard-deviation increase

in our measure of relative sentiment is associated with a 0.175-standard-deviation increase in the Shiller relative sentiment, with a *t*-statistic of 2.54. This positive correlation suggests that our sentiment measure is related to broader survey-based indicators of investors' beliefs about others' sentiment, while also capturing distinct variation that likely reflects the higher-frequency, market-based nature of our data.

In sum, these figures provide three key stylized facts. First, the linguistic content of HOB posts matches the conceptual definition of HOB and is distinct from FOB posts only in ways that meaningfully reference others. Second, the overall frequency of HOB expression is stable over time but varies substantially across firms. Third, subjective and own sentiments exhibit large and economically meaningful fluctuations, and the gap between them widens precisely in periods of sharp market reassessment. These patterns motivate our subsequent analysis of the determinants of HOB expression and the sentiment investors attribute to others.

E. Summary Statistics

Table 1 reports summary statistics for the firm-week panel used in our analysis. Posting activity is highly right skewed. The average firm-week contains 121 posts, but the median is only 24 posts, and the 75th percentile is 68 posts. A similar pattern holds for higher-order HOB messages. Firms receive on average 16 HOB posts per week, while the median is 2 posts and the 75th percentile is 7 posts. The much large number of total posts relative to HOB posts indicates that a significant number of posts centers on discussion about others' beliefs. In addition, while Figures 1 and 2 show that the fraction of HOB posts exhibits little variation over time, Table 1 demonstrates that posting activity displays substantial cross-sectional heterogeneity. Most firms receive only a modest number of messages, whereas a small subset attracts disproportionately large volumes of discussion.

The sentiment measures also display clear patterns. *Own Sentiment*, based on users' self-reported bullish or bearish tags, is positive on average (0.298) with a standard deviation of 0.488, suggesting that users tend to express mildly more optimistic views. *Subjective_Sentiment*, which captures the sentiment attributed to others, also displays

positive average values (0.450). In our later analysis, we standardize all variables for easier interpretation except for returns.

IV. Determinants of Subjective Sentiments

A. Fraction of HOB

We first ask the question: when are investors more likely to express their beliefs about others? If investors pay closer attention to what others think, theories of social learning and narrative transmission predict a greater prevalence of higher-order commentary (Hirshleifer and Teoh 2003; Allen et al. 2006; Alevy et al. 2007; Bikhchandani et al. 2024). Identifying the conditions under which HOB posting rises therefore helps us understand when social inference becomes more important in investor communication.

Table 2 regresses the fraction of HOB posts on belief measures and market conditions. Column (1) controls for the two sentiment measures. Following Cookson and Niessner (2020), in column (2), we further control for the *Disagreement*, which is defined as the standard deviation of FOB tags within firm and year-week. In columns (3) to (5), we further include current excess return, valuation, and other firm characteristics. Across all columns, we control for firm fixed effects and year-week fixed effects.

Focusing on the fully controlled specification in column (5), two patterns stand out. First, the fraction of HOB posts does not seem to depend on how optimistic themselves are but is higher when they perceive others as more pessimistic. In particular, each standard-deviation increase in relative sentiment is associated with roughly a 0.25 percentage point decrease in the HOB share. Second, the fraction of HOB posts is lower when disagreement is higher: each standard-deviation increase in disagreement is associated with roughly a 0.85 percentage point decrease in the HOB share. This is consistent with the mechanism of echo chamber (Cookson et al. 2023) such that people more like to express confirmatory ideas when it is easier to find other users who would hold the same views.

Second, the fraction of HOB posts is higher when contemporaneous returns are low and when E/P is high. Column (5) shows that a 10% lower return is associated with roughly a 0.09 percentage point increase in the HOB share, while a one-standard-deviation increase

in E/P is associated with roughly a 0.26 percentage point increase. That is, HOB posting rises both when recent price performance is weak and when valuation ratios indicate relatively low firm valuation.

B. Subjective Sentiment

We next study how subjective sentiment, that is, the sentiment attributed to others, co-moves with firm characteristics while controlling for investors' own stated sentiment. Table 3 regress subjective sentiment on the same set of firm characteristics and fixed effects in Table 2. Across all specifications, subjective sentiment is positively associated with own sentiment: a one-standard-deviation increase in own sentiment corresponds to roughly a 0.2-standard-deviation increase in subjective sentiment, consistent with the time-series co-movement in Figure 5. However, subjective sentiment continues to vary with market and firm characteristics even after controlling for investors' own views, indicating that investors' beliefs about others' beliefs differ from their own belief in a systematic manner.

In particular, subjective sentiment is also strongly decreasing in both disagreement and idiosyncratic volatility. These negative coefficients indicate that when beliefs among investors are more dispersed or when stock-specific uncertainty is high, investors attribute more pessimistic views to others. This pattern is consistent with the evidence in Gorodnichenko and Yin (2025), who show that relative sentiment is lower when subjective uncertainty is high. This reflects the tendency for investors to assume that others react more pessimistically when the information environment becomes noisier.

In addition, subjective sentiment is also higher when contemporaneous returns are high: from column (4), a one-standard-deviation higher return (corresponding to 16%) is associated with roughly a 0.08-standard deviation higher subjective sentiment. In addition, *Subjective Sentiment* is also positively correlated with E/P: a one-standard-deviation higher E/P is associated with roughly a 0.02-standard deviation higher subjective sentiment.

Therefore, investors tend to believe that others are more optimistic when return is higher or fundamental is strong.[2]

Taken together, Tables 2 and 3 show that both the frequency of HOB posting and the sentiment investors attribute to others respond systematically to basic belief and uncertainty measures. HOB posting rises when investors ascribe others as more pessimistic or when there is less disagreement across investors. Subjective sentiment moves with investors' own stated beliefs, but becomes more negative when disagreement or idiosyncratic volatility is higher, even after controlling for personal views. Beyond these baseline patterns, both measures react strongly with returns and valuation signals. In particular, the fraction of HOB posts increases when return is low or E/P is high, while subjective sentiment becomes more positive when both return and E/P are higher.

V. Subjective Sentiments and Market Activities

A. Retail Trading Activities

How investors react to beliefs of others have been a controversial topic. Prior work highlights that investors may respond to the beliefs they attribute to others in two distinct ways. On the one hand, investors may follow or amplify others' expected actions when they view others' beliefs as informative, resembling a momentum-style response. Such behavior arises in settings where investors believe others possess useful information or underreact to news (Hong and Stein 1999), in models of informational cascades (Bikhchandani et al. 1992; Avery and Zemsky 1998; Alevy et al. 2007), models with dynamic strategic coordination (Allen et al. 2006; Bacchetta and Van Wincoop 2006) in empirical evidence showing that retail traders often trade in the direction of perceived sentiment (Barber, Odean, and Zhu 2009). On the other hand, investors may lean against others' perceived expectations when they interpret observed pessimism or overreaction as excessive. This contrarian response appears in social-learning models where agents offset correlated or overweighted signals (Park and Sabourian 2011; Acemoglu et al. 2011; Eyster

[2] The relatively modest economic magnitudes are expected given the measurement noise inherent in standardized text-based sentiment measures. Cookson and Niessner (2020) similarly find that disagreement responds statistically, but only weakly, to firm characteristics and daily return patterns.

and Rabin 2014) and in recent theories showing that traders adjust their interpretation of price signals depending on how they perceive others to extrapolate (Bastianello and Fontanier 2025; Gorodnichenko and Yin 2025).

Our measure of higher-order sentiment allows us to examine these two channels directly. By separately identifying investors' own sentiment, their subjective sentiment about others, and the intensity with which they engage in higher-order reasoning (fraction of HOB posts), we can distinguish whether retail trading responds to others' perceived expectations in a momentum-like manner or instead reflects a contrarian stance toward others' beliefs. In addition, studying whether StockTwits narratives relate to trading behavior also helps assess whether these posts are reflected in actual trading activity, or merely cheap talks.

Table 4 gives the results of regressing retail-order imbalance on the sentiment measures. Retail order imbalance is defined as the ratio of the difference between retail purchasing volume and retail selling volume and total share outstanding. From column (6) where we include the full set of controls, retail order imbalance increases with own sentiment: a one-standard-deviation rise in investors' own sentiment is associated with roughly a 0.1-standard-deviation increase in retail buying. In this sense, retail traders tend to buy more when their own outlook is optimistic. In comparison, controlling for investors' own sentiment, relative sentiment enters modestly negatively, and the effect is economically small but systematic: a one-standard-deviation increase in relative sentiment reduces retail buying by about 0.012 standard deviations. This indicates that retail traders buy slightly more when they perceive others as more pessimistic, consistent with a mild contrarian response to attributed beliefs.

Table 5 examines how relative sentiment affects the composition of retail trading. Column (2) shows that higher relative sentiment compresses retail trading volume: a one-standard-deviation increase in relative sentiment is associated with roughly a 0.42-standard-deviation decline in total retail order flow, indicating a sizable increase in retail participation when investors perceive others as more pessimistic. Columns (3) and (4) show that this decline reflects symmetric adjustments on both sides of the market. Higher relative

sentiment is associated with a 0.21-standard-deviation reduction in retail buy orders and a 0.20-standard-deviation reduction in retail sell orders, suggesting that investors scale back both buying and selling rather than shifting positions across sides. By contrast, own sentiment strongly increases retail trading activity across all specifications, indicating that investors' own outlook remains a primary driver of retail participation.

The modest average association between retail order imbalance and relative sentiment masks substantial heterogeneity across information environments. In Table 6, we study how retail order imbalance moves with relative sentiments in different condition.

First, retail investors are substantially more contrarian when uncertainty is high. Columns (1) - (3) show that the interaction between relative sentiment and measures of uncertainty: higher-order-belief (HOB) uncertainty, return volatility, and idiosyncratic volatility, is large and negative. Quantitatively, moving from low to high uncertainty amplifies the contrarian response by roughly 0.10 to 0.15 standard deviations of retail order imbalance per one-standard-deviation increase in relative sentiment. Relative to the average effect documented in Table 4, these interaction terms are an order of magnitude larger, indicating that most of the contrarian response is concentrated in high-uncertainty states rather than being uniform over time.

This mechanism is consistent with social-learning models in which agents place more weight on others' beliefs when those beliefs are perceived to be precise. In particular, when uncertainty is low, public signals, which aggregates others' beliefs, are more incorporated into own belief. As a result, discrepancy between first-order and higher-order beliefs are narrowed, leading higher-order beliefs less weighted in investors' consideration (e.g., Park and Sabourian, 2011; Acemoglu et al., 2011; Eyster and Rabin, 2014).

Second, retail investors are also more contrarian when retail trading activity itself is high. Column (4) shows that in firm-weeks with elevated retail trading intensity, the interaction between relative sentiment and the high-retail indicator is strongly negative, with a magnitude comparable to that of the volatility-based interactions. A one-standard-deviation increase in relative sentiment is associated with a decline in retail order imbalance of roughly 0.10 standard deviations in high-retail-activity periods. Presumably,

when retail participation is elevated, investors infer that trading is more likely driven by sentiment or noise rather than new information, reducing the informational content of others' beliefs and strengthening contrarian behavior.

In the end, retail trading is more contrarian to subjective sentiment when the stocks appear to be less liquid. From columns (5) to (7), a one-standard-deviation increase in relative sentiment is associated with an additional decline in retail order imbalance of roughly 0.14 standard deviations in when the stocks in a given week have smaller size or larger bid-ask spread.

Taken together, the results show that retail trading reflects both investors' own sentiment and their perceptions of others' sentiment, but the strength and even the direction of these responses vary across environments. On average, retail traders buy more when they are optimistic themselves but lean slightly against the sentiment they attribute to others. This contrarian response becomes much stronger in environments where others' beliefs are likely viewed as less informative, i.e., when uncertainty is high, when retail trading itself is more intense, or when liquidity gets depressed.

B. Return Dynamics

The preceding analysis shows that higher-order beliefs are systematically related to retail trading behavior, with relative sentiment associated with contrarian retail order flow. A natural next question is whether these belief-based measures are informative about subsequent return dynamics. We continue to examine whether Relative Sentiment predicts short-horizon returns, and whether such predictability varies across firms with different characteristics.

In Table 7, we first study the predictability of the sentiment measures in the current week on returns in the next week in Panel A and over the next three weeks in Panel B. Frist, consistent with the large literature documenting that investor optimism forecasts subsequent reversals, including Baker and Wurgler (2006) and Tetlock (2007). In Panel A column (1), we find that on average own sentiment negatively predict return in the next week. In particular, each standard deviation higher own sentiment in the current week predicts a 4.1% lower return in the next week. From Panel B, the predictability is weaker,

with each standard deviation higher own sentiment predicting an insignificant 3.4% negative return over the next three weeks.

In contrast, the sign is opposite for subjective sentiment. In Panel A column (1), each standard deviation higher subjective sentiment predicts a 5.5% higher return in the next week. From Panel B, return continues to increase over the next two weeks: each standard deviation higher subjective sentiment in the current week predicts a 11.9% higher total return from next week to three weeks later. With the estimates highly significant.

In the end, columns (2) to (11) in Table 7 study the predictability of sentiment measures on returns for each sub-sample split by retail intensity, uncertainty, and liquidity. The results are similar to those for retail trading. That is, the predictability of the sentiment measures is stronger when the firms have more retail trading intensity or gets less liquid, or when uncertainty is higher.

These findings about return predictability and retail trading point to a dynamic interpretation of the return predictability associated with higher-order beliefs. Subjective sentiment is positively related to future returns in settings where retail investors are also likely engaging in contrarian trading. One possibility is that contrarian trading of retail investors depresses current price, leading to reversal in the following period. Alternatively, subjective sentiment can arise following strong contemporaneous returns, reflecting investors' beliefs that others are optimistic after recent price increases. Meanwhile, contrarian retail trading dampens immediate price adjustment, slowing convergence to fundamentals. As a result, prices continue to drift upward in subsequent weeks, generating short-horizon momentum. To further explore the possible mechanism, we continue to examine the time-series evolution of returns around sentiment fluctuations.

In Figure 7, we plot the return coefficients on subjective sentiment and own sentiment at horizons from the two weeks earlier to four weeks ahead. The specification is

$$\boldsymbol{r_{i,t+h} = \alpha_{t+h} ss_{i,t} + \beta_{t+h} os_{i,t} + X_{i,t}\gamma + \epsilon_{i,t+h},}$$

where for stock $\boldsymbol{i}$ in week $\boldsymbol{t}$, $\boldsymbol{r_{i,t+h}}$ is the return in week $\boldsymbol{t+h}$, $\boldsymbol{ss_{i,t}}$ and $\boldsymbol{os_{i,t}}$ are respective subjective sentiment and own sentiment in week $\boldsymbol{t}$, and $\boldsymbol{X_{i,t}}$ contains the controls four

weeks ago. $\boldsymbol{\alpha_{t+h}}$ and $\boldsymbol{\beta_{t+h}}$ therefore measure the relationship between the sentiment measures and return in week $\boldsymbol{t+h}$.

Several patterns emerge. First, both subjective and own sentiment is positively associated with contemporaneous returns, and the association between own sentiment and contemporaneous returns is much stronger. Specifically, a one-standard-deviation increase in subjective sentiment is associated with approximately 10% higher returns in the same week. Meanwhile, a one-standard-deviation increase in own sentiment is associated with approximately 30% higher returns in the same week.

Second, consistent with the findings in Table 7, after the week with higher subjective sentiment, returns continue to be positive for three more weeks, after which return converges back to zero. On the other hand, own sentiment predicts negative return in the next week. The reversal pattern is consistent with investors overreacting to own sentiment, leading to over-pricing. Meanwhile, beyond week $\boldsymbol{t+1}$, own sentiment does not predict returns in further future. This difference between return dynamics around subjective sentiment and own sentiment fluctuation also suggests that sentiment about others captures a channel that is distinct from traditional sentiment measures and cannot be reduced to first-order belief extrapolation. That is, subjective sentiment is unlikely a mere derivative of own sentiment, and the two sentiments have different impacts on trading behaviors, which lead to different return dynamics.

C. Discussion

Although subjective sentiment is associated with more contrarian retail trading, it is not associated with lower contemporaneous returns. Therefore, the findings do not support an interpretation in which contrarian retail trading depresses prices on impact and generates subsequent return reversals.

Instead, the evidence is consistent with a liquidity-provision channel. Contrarian retail trading need not exert negative net price pressure at impact. Rather, retail investors may supply liquidity against prevailing positive price movements, partially absorbing order flow without fully offsetting it. This behavior slows the adjustment of prices toward their

longer-run levels, allowing returns to continue drifting in the short run, particularly in environments with high retail participation and low liquidity.

Mapped to our findings, which can be summarized into 1) subjective sentiment is stronger when current return is higher, 2). subjective sentiment is associated with less retail net purchase, and 3), subjective sentiment predicts higher return going forward. Therefore, the documented dynamics are consistent with this mechanism: when returns are higher, investors tend to believe that others are too optimistic. They purchase less in net, which dampens the price to reach to the fundamental level. As time goes by, price slowly converges to a higher level.

This mechanism is closely related to the logic in Luo et al. (2025), who show that contrarian trading by liquidity-supplying investors can dampen short-run price responses and generate momentum-like return continuation when informed trading pressure is not fully arbitraged away. In this interpretation, contrarian retail trading acts as a friction that smooths price movements rather than immediately correcting mispricing.

Taken together, Table 6 and Figures 7 show that subjective beliefs about others' sentiment and investors' own sentiment have sharply different implications for return dynamics. While investors' own optimism predicts subsequent reversals, optimism attributed to others predicts short-horizon return continuation. Consistent with Laarits and Sammon (2025) and Luo et al. (2025), these findings suggest that contrarian retail trading in response to beliefs about others can slow price adjustment, allowing momentum-like dynamics to emerge, particularly in stocks with higher retail participation, lower liquidity, and weaker institutional trading presence.

VI. Robustness of the Results

The Online Appendix provides a broad set of robustness checks that assess the stability of our findings across alternative samples, specifications, and measurement choices. These exercises are designed to verify that the documented relationships between subjective sentiment, retail trading, and returns are not driven by particular time periods, modeling assumptions, or empirical design choices.

First, we examine robustness across subsamples and sample periods. In Tables A.1 to A.3, we show that the patterns for higher-order posting, subjective sentiment, and retail trading hold before and after key market episodes, including splits around 2018, the COVID period, and the post-2022 market environment. While magnitudes vary across subsamples, the qualitative relationships between sentiment about others, contrarian retail trading, and return dynamics remain stable, indicating that our results are not driven by a specific market regime.

Second, because relative sentiment is defined as the difference between subjective sentiment and own sentiment, one concern is that its association with trading and returns could mechanically reflect the negative loading on own sentiment. All our main specifications explicitly control for own sentiment, so the estimated coefficient on relative sentiment captures variation orthogonal to investors' own views. Nevertheless, in Table A4, we further verify that the results are preserved when replacing relative sentiment with subjective sentiment directly. Across these specifications, the qualitative relationships between beliefs about others, retail trading, and returns remain unchanged.

Lastly, in Table A.5, we explore alternative empirical specifications and fixed-effect structures. The main results are robust to using different combinations of firm, time, and two-way fixed effects, as well as to alternative clustering schemes for standard errors.

VII. Conclusion

This paper studies how investors perceive the sentiment of others and how these perceptions relate to communication, trading, and price dynamics in financial markets. Using more than 46 million StockTwits posts, we apply language models to distinguish messages expressing an author's own outlook from those describing the reasoning or expected actions of others. This distinction allows us to construct firm-week measures of subjective sentiment, own sentiment, and subjective disagreement, objects that are central in theory but have been difficult to observe empirically.

We show that references to others are pervasive and systematically differ from investors' own views, and that subjective sentiment varies with disagreement, valuation-return combinations, and market uncertainty. Linking these beliefs to market outcomes, we

find that retail traders buy more when their own sentiment is optimistic, but tend to trade against the sentiment they attribute to others. Importantly, this relationship is state dependent: the contrarian response to beliefs about others is stronger when uncertainty is high, retail participation is elevated, and liquidity is lower. We further show that sentiment about others is positively associated with short-horizon future returns, in contrast to own sentiment, which predicts reversals. Taken together, these findings provide large-scale evidence that higher-order beliefs are distinct from first-order sentiment and play a systematic, state-dependent role in shaping retail trading behavior and short-run price dynamics.

Our results also open several avenues for future research. One natural direction is to combine our higher order sentiment measures with topic-modeling approaches used in macro-finance, such as Kelly, Manela, and Moreira (2021), to study whether investors discuss others' reasoning more intensively under different macroeconomic regimes or narrative environments. Another is to integrate our measures with investor-level or platform-level network structures to examine how access to social information shapes trading responses, for example, whether contrarian behavior weakens when investors are better connected or face lower search frictions. Finally, because language models allow relational content to be measured across many settings, future work can extend our approach to professional analysts, corporate disclosures, or international markets to better understand how perceptions of others' beliefs shape economic decisions more broadly.

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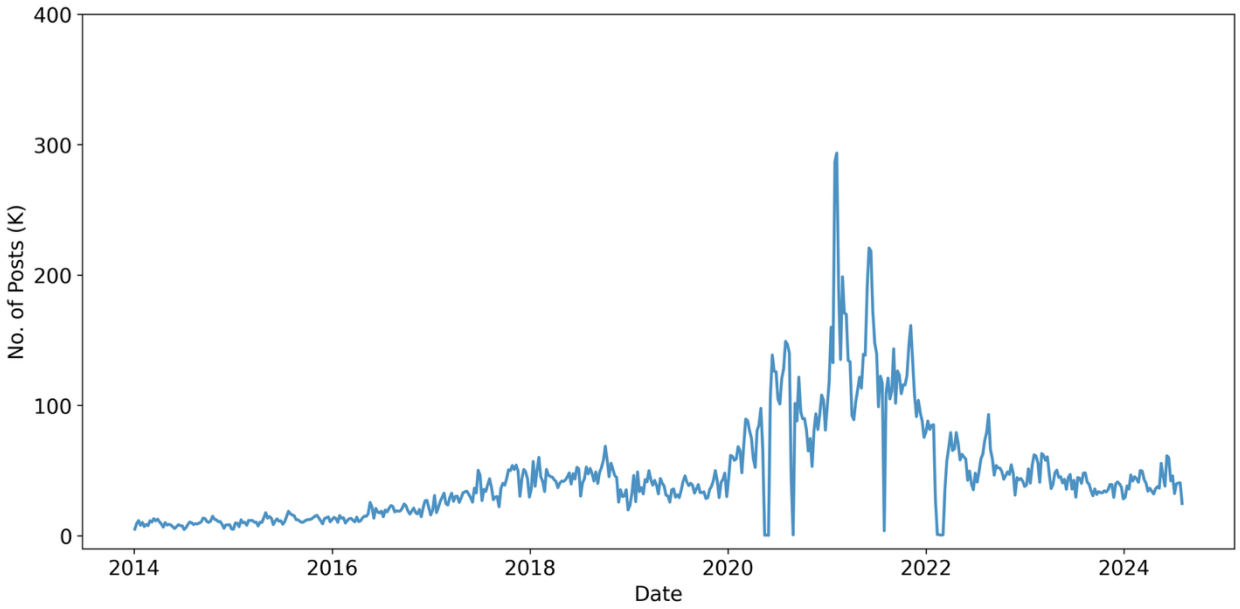
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Figure 1: Number of Weekly Posts



Note: This figure plots the weekly time series of the total number of posts (in thousands) on our final sample of StockTwits from January 2014 to July 2024.

Figure 2: Word Clouds

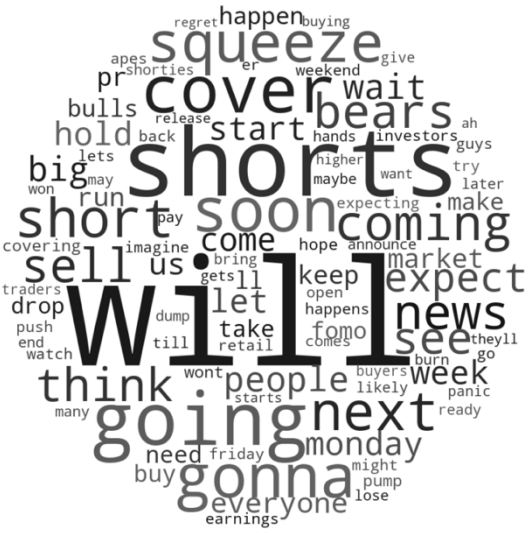
A: FOB



B: HOB



C: HOB - FOB



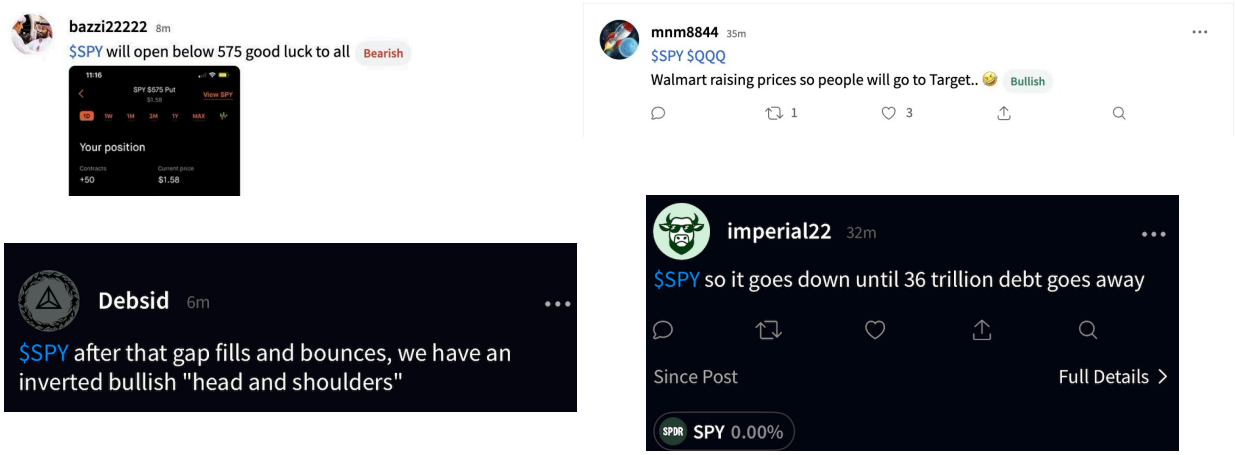
D: Expectation - Rationalization



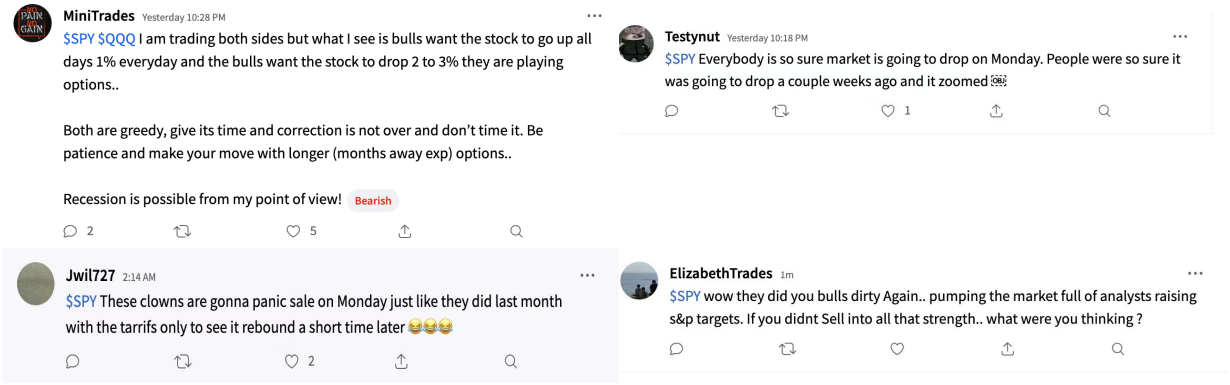
Note: This figure presents word clouds constructed from StockTwits messages. Panel A shows FOB messages, which express investors' own views without mentioning others' beliefs or actions. Panel B displays a word cloud based on HOB messages—posts that explicitly refer to others' beliefs or actions. Panel C highlights language that is more frequently used in HOB messages than in FOB messages, based on the difference in word frequencies between the two groups. Panel D demonstrates words that have higher frequency in form expectation HOB messages than in rationalized current HOB messages.

Figure 3: Examples of Posts

A: FOB



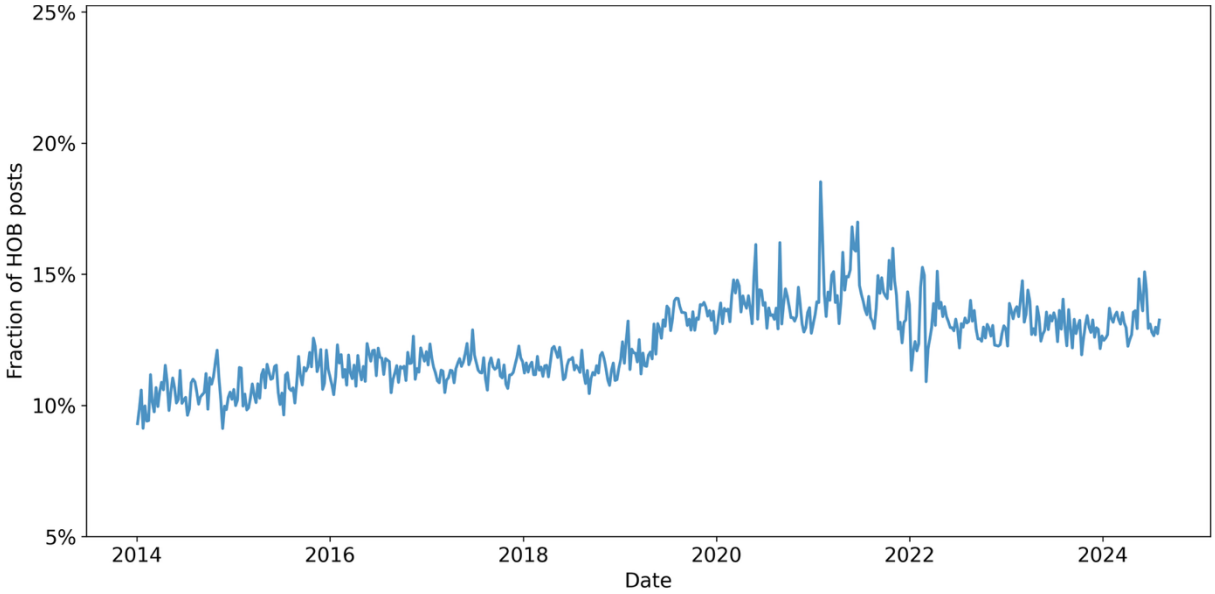
B: HOB



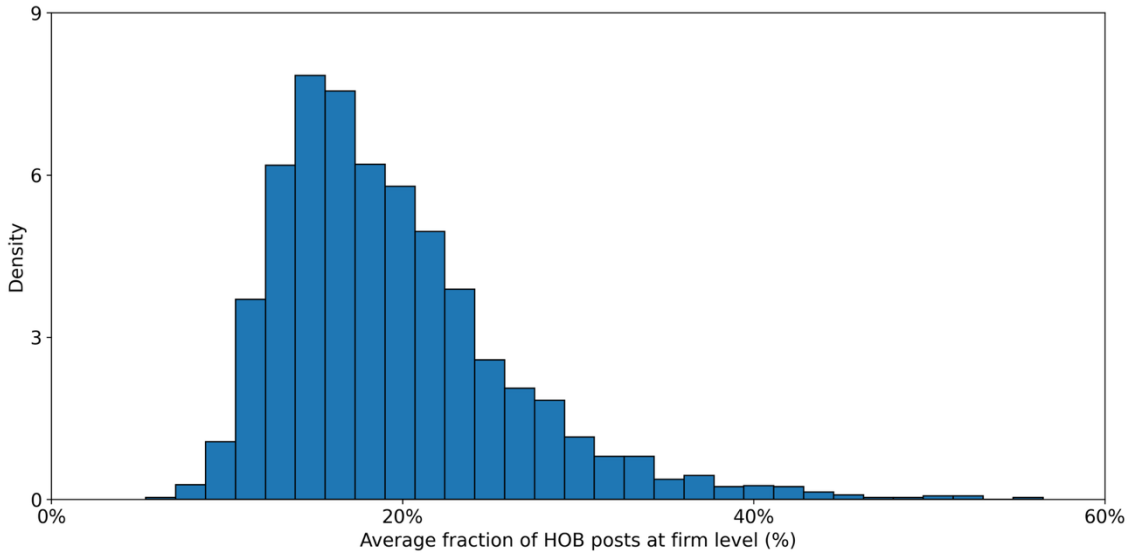
Note: Panel A and Panel B of this figure respectively give examples of the message classified as FOB and HOB.

Figure 4: Fraction of HOB Posts

A: Time-Series Evolution



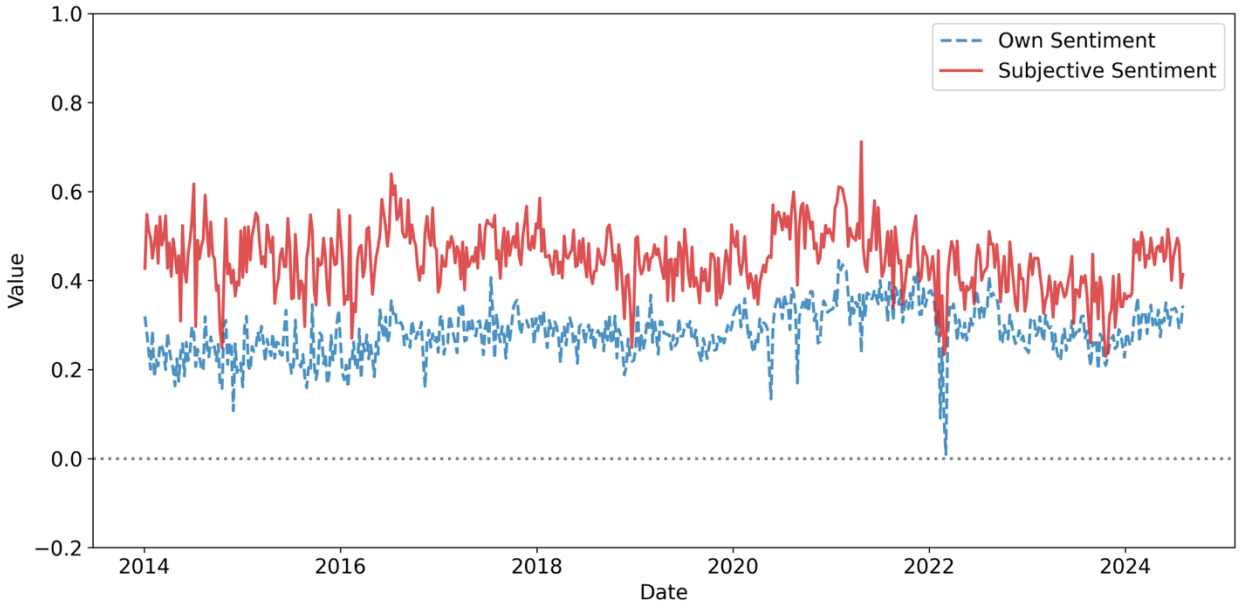
B: Cross-Section of Firm Averages



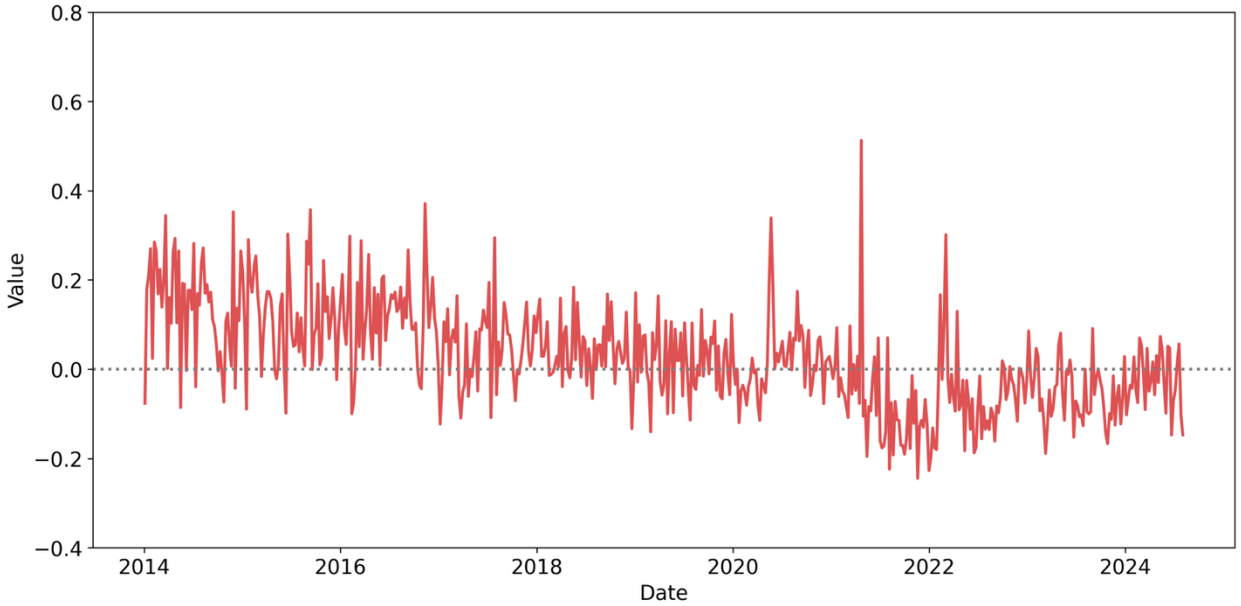
Note: Panel A shows the weekly fraction of posts that references to others' belief or actions (Fraction HOB) in our sample from January 2014 to July 2024. Panel B plots the distribution of the firm-level average fraction of higher-order-belief (HOB) messages. For each firm, we compute the mean share of posts classified as HOB, requiring at least three observations per firm.

Figure 5: Time Series of Subjective, Own and Relative Sentiment

Panel A: Subjective and Own Sentiment

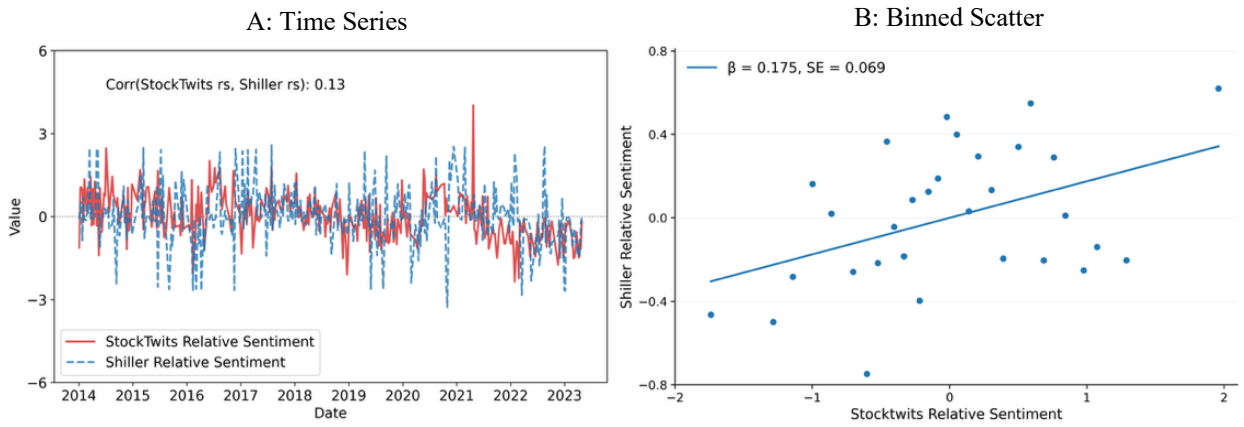


Panel B: Relative sentiment



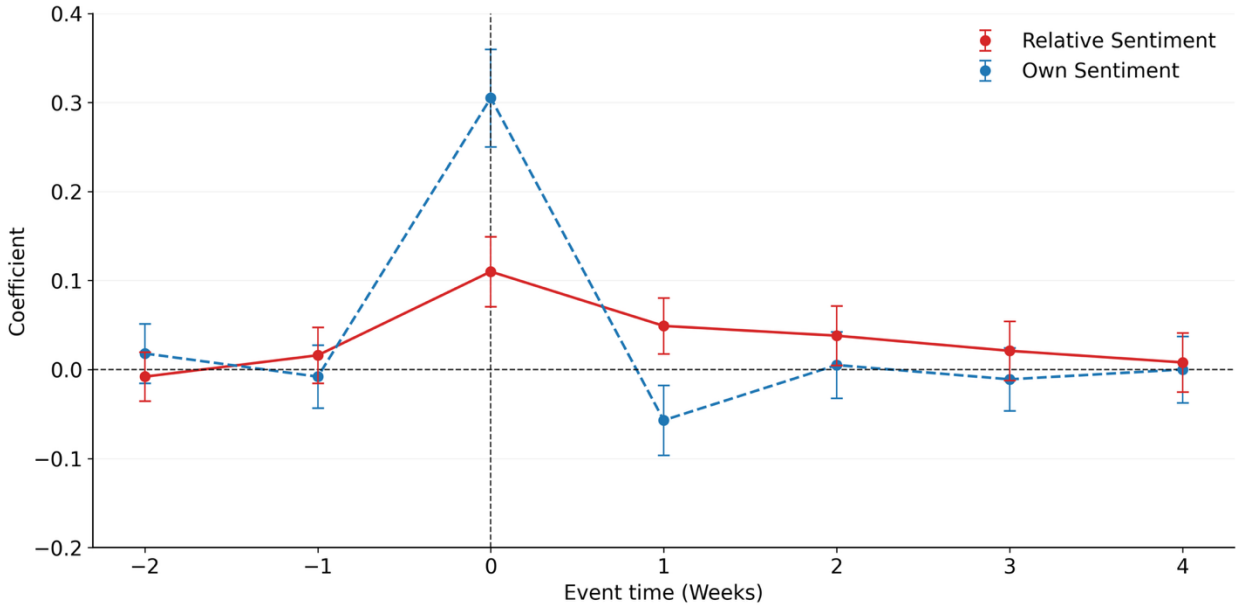
Note: This figure plots the weekly time series of own sentiment (*Own Sentiment*), subjective sentiment (*Subjective sentiment*) and relative sentiment (*Relative sentiment*) from January 2014 to July 2024. Panel A shows the objective and subjective sentiment, where the blue dashed line represents own sentiment and the green dotted line represents subjective sentiment. Panel B displays the weekly time series of Relative Sentiment, constructed as the difference between standardized subjective sentiment (*Subjective sentiment*) and standardized own sentiment (*Own Sentiment*).

Figure 6: Stocktwits Relative Sentiment and Shiller Relative Sentiment



Note: This figure illustrates the relationship between Stocktwits Relative Sentiment and Shiller Relative Sentiment measure. Stocktwits Relative Sentiment is constructed using the revisualized values from regressing value-weighted *Relative Sentiment* on value-weighted *Own Sentiment,* capturing the market-level Relative Sentiment component. Shiller Relative sentiment is measured as the residual from regressing *High order belief* on *1-year expectation.* Panel A presents the time series of Stocktwits Relative Sentiment and Shiller Relative Sentiment from January 2014 to April 2023 with a correlation about 0.13. Panel B shows a binscatter plot of Shiller Relative Sentiment on Stocktwits Sentiment. Standard errors are adjusted *a la* Newey-West with three lags.

Figure 7: Return Dynamics Relative Sentiment and Own Sentiment



Note: These figures present the weekly return dynamics. The red solid line plots regression coefficients on Relative Sentiment from regressions of annualized log stock excess returns (RET) from T-2 to T+4. The blue dash line plots regression coefficients on Own Sentiment with the same specification. The regressions control for Fraction HOB, Disagreement, past 4 weeks excess returns exclude the recent 1 week (MOM-1M), one-week lagged turnover (Lag. Turnover), last month idiosyncratic volatility (IVOL), earnings to price ratio (E/P), book to market (BM), profitability (PROF), investment (INV), leverage (LEV). All regressions include firm and yearwk fixed effects with standard errors double-clustered by firm and yearwk. All 95% confidence intervals show on the graph.

Table 1: Statistic Summary

	Mean	SD	25%	50%	75%	N
N Posts	120.959	889.105	10.000	24.000	68.000	210645
N HOB Posts	15.974	152.023	1.000	2.000	7.000	210645
Fraction HOB	0.150	0.100	0.086	0.125	0.182	210645
Subjective Sentiment	0.450	0.673	0.000	0.667	1.000	210645
Own Sentiment	0.298	0.488	0.000	0.000	0.859	210645
Relative Sentiment	0.000	1.231	-0.962	-0.169	1.429	210645
HOB Uncertainty	0.128	0.056	0.100	0.100	0.137	210645
Disagreement	0.538	0.382	0.000	0.603	0.882	210645
Market Cap	30.813	146.629	0.660	0.467	5.412	210645
BM	0.617	0.807	0.159	0.344	0.756	210645
INV	0.420	1.246	-0.088	0.066	0.398	210645
PROF	-0.302	0.496	-0.489	-0.132	0.026	210645
LEV	0.481	0.261	0.256	0.485	0.690	210645
E/P	-0.451	1.189	-0.370	-0.067	0.021	210645
RET	-0.001	0.155	-0.059	-0.001	0.053	210645
Ret Volatility	0.050	0.082	0.021	0.035	0.057	210645
MOM-1M	-0.021	0.279	-0.132	-0.011	0.095	210645
TURN	0.196	0.449	0.038	0.077	0.160	210645
IVOL	0.040	0.035	0.019	0.030	0.048	210645
Retail Order Imbalance	0.288	1.408	-0.108	0.028	0.291	181561
Total Retail Order	11.968	36.341	0.940	2.417	6.749	181561
Retail Buy Order	6.144	18.696	0.468	1.222	3.460	181561
Retail Sell Order	5.812	17.589	0.456	1.176	3.295	181561

Note: N Posts, N HOB Posts and Fraction HOB denotes the total number of posts, the number of posts mentioned others' belief (higher order belief, HOB posts), and the fraction of HOB posts relative to total posts at firm week level, respectively. Subjective Sentiment and Own Sentiment measures the average of subjective sentiment (HOB sentiment) and own sentiment (FOB sentiment) at firm week level. The Disagreement shows the standard deviation of investors' Own Sentiment. The HOB Uncertainty measures as the average of HOB posts uncertainty score at firm week level. The Retail Order Imbalance is the retail investors net order flow scaled by the share outstanding. The Total Retail Order, Retail Buy Order and Retail Sell Order represent the total retail order flow, retail buying order flow and retail selling order flow, respectively. All of these order flow variables are scaled by the share outstanding. Other standard variables include: log weekly excess returns (RET), firm week turnover (Turnover), return volatility (Ret Volatility), cumulative return in the past 4 weeks exclude recent week (MOM-1M), idiosyncratic volatility (IVOL), book-to-market ratio (BM), market capitalization in $ billion (Market Cap), investment (INV), profitability (PROF), leverage (LEV), earnings to price (E/P), analyst dispersion (Analyst Dispersion). All variables are winsorized at the 1%-99% level.

Table 2: Fraction of HOB

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:			Fraction HOB			
Subjective Sentiment	0.002	-0.195***	-0.193***	-0.197***	-0.200***	-0.200***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)	(0.028)
Own Sentiment	0.208***	0.129***	0.133***	0.135***	0.179***	0.179***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Disagreement		-0.866***	-0.878***	-0.872***	-0.850***	-0.850***
		(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
RET			-0.894***	-0.945***	-0.865***	-0.967***
			(0.139)	(0.143)	(0.145)	(0.156)
E/P				0.357***	0.256***	0.238***
				(0.052)	(0.055)	(0.056)
RET x E/P						-0.187***
						(0.069)
BM				0.081	0.049	0.048
				(0.061)	(0.061)	(0.061)
SIZE				-0.649***	-0.839***	-0.829***
				(0.207)	(0.212)	(0.213)
PROF					0.215***	0.219***
					(0.064)	(0.065)
INV					-0.118***	-0.118***
					(0.042)	(0.042)
LEV					-0.103	-0.102
					(0.083)	(0.083)
MOM-1M					0.326***	0.329***
					(0.092)	(0.092)
IVOL					-0.574***	-0.574***
					(0.034)	(0.034)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	210136	210136	210136	210136	210136	210136
R-sq	0.183	0.188	0.188	0.189	0.191	0.191

Note: This table examines the fraction of HOB posts (Fraction HOB) relates to higher order belief, first order belief, disagreement measures, and valuation metrics. In column (1), we regress Fraction HOB on Subjective Sentiment and Own Sentiment. Columns (2) and (3) further include the disagreement in own sentiment (Disagreement) and contemporaneous returns (RET). In column (4), we add valuation measures such as earnings to price ratio (E/P), book to market (BM), log market capitalization (SIZE). Column (5), additionally control firm characteristics including profitability (PROF), investment (INV), leverage (LEV), as well as past 4 weeks excess returns exclude the recent 1 week (MOM-1M), and one month lagged idiosyncratic volatility (IVOL). Column (6) includes the interaction variable (RET × E/P). All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 3: Subjective Sentiment

	(1)	(2)	(3)	(4)	(5)
Dep Var:			Subjective Sentiment		
Own Sentiment	0.194***	0.194***	0.194***	0.195***	0.195***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Fraction HOB	-0.194***	-0.193***	-0.197***	-0.201***	-0.201***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Disagreement	-0.684***	-0.681***	-0.681***	-0.682***	-0.682***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
RET		0.082***	0.094***	0.088***	0.081***
		(0.012)	(0.012)	(0.012)	(0.013)
E/P			0.020***	0.021***	0.020***
			(0.004)	(0.004)	(0.004)
RET x E/P					-0.012*
					(0.007)
BM			-0.001	0.001	0.001
			(0.004)	(0.005)	(0.005)
SIZE			-0.126***	-0.118***	-0.117***
			(0.014)	(0.015)	(0.015)
PROF				0.001	0.002
				(0.005)	(0.005)
INV				-0.004	-0.004
				(0.003)	(0.003)
LEV				-0.001	-0.001
				(0.005)	(0.005)
MOM-1M				-0.045***	-0.045***
				(0.008)	(0.008)
IVOL				-0.009***	-0.009***
				(0.003)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes
N	210136	210136	210136	210136	210136
R-sq	0.185	0.185	0.185	0.185	0.186

Note: This table examines the subjective sentiment (Subjective Sentiment) relates to first order belief, disagreement measures, and valuation metrics. In column (2), we regress subjective sentiment on own sentiment (Own Sentiment), fraction of HOB posts (Fraction HOB), the disagreement in own sentiment (Disagreement). Columns (3) further include contemporaneous returns (RET). In column (3), we add valuation measures such as earnings to price ratio (E/P), book to market (BM), log market capitalization (SIZE). Column (4), additionally control firm characteristics including profitability (PROF), investment (INV), leverage (LEV), as well as past 4 weeks excess returns exclude the recent 1 week (MOM-1M), and one month lagged idiosyncratic volatility (IVOL). Column (5) includes the interaction variable (RET × E/P). All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 4: Retail Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
	Retail Order Imbalance					
Relative Sentiment	-0.106***	-0.025***	-0.033***	-0.010***	-0.010***	-0.012***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Own Sentiment		0.131***	0.112***	0.140***	0.124***	0.132***
		(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
Fraction HOB				-0.733***	-0.638***	-0.643***
				(0.040)	(0.039)	(0.040)
Disagreement				0.222***	0.189***	0.174***
				(0.012)	(0.012)	(0.012)
MOM-1M					-0.479***	-0.343***
					(0.040)	(0.036)
TURN					0.354***	0.318***
					(0.043)	(0.042)
IVOL					0.032***	0.016*
					(0.009)	(0.009)
E/P						-0.160***
						(0.020)
BM						-0.051***
						(0.012)
SIZE						-0.275***
						(0.035)
PROF						0.062***
						(0.015)
INV						-0.004
						(0.009)
LEV						-0.012
						(0.012)
Firm FE	No	No	Yes	Yes	Yes	Yes
Yearwk FE	No	No	Yes	Yes	Yes	Yes
N	181030	181030	180583	180583	180583	180583
R-sq	0.006	0.011	0.094	0.099	0.113	0.123

Note: This table examine how subjective sentiment (Relative Sentiment) affects the retail net order flow (Retail Order Imbalance). In column (1), we regress Retail Order Imbalance on Relative Sentiment only without any fixed effect. Column (2) add controls for Own Sentiment without any fixed effect. Column (3) follow the same regression specification but add firm and yearwk fixed effects. Column (4), add controls for the fraction of HOB posts (Fraction HOB), disagreement in own sentiment (Disagreement). Column (5) further controls for past 4-week excess returns exclude the recent week (MOM-1M), the one-week lagged turnover (Lag. Turnover) and last month idiosyncratic volatility (IVOL). Column (6) we control for valuation measurements such as earning to price ratio (E/P), book to market ratio (BM), log market capitalization (SIZE), and firm characteristics including profitability (PROF), investment (INV) and Leverage (LEV). All variables are winsorized at 1% - 99% level and standardized except MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 5: Retail Trading Activities

Dep Var:	(1)	(2)	(3)	(4)	(5)	(6)
	Total Retail Order Flow		Retail Buy Order		Retail Sell Order	
Relative Sentiment	-1.314***	-0.412***	-0.676***	-0.212***	-0.636***	-0.199***
	(0.108)	(0.068)	(0.055)	(0.035)	(0.052)	(0.032)
Own Sentiment	4.338***	3.937***	2.232***	2.046***	2.099***	1.885***
	(0.238)	(0.197)	(0.122)	(0.102)	(0.116)	(0.095)
Fraction HOB		-17.526***		-9.125***		-8.383***
		(1.184)		(0.611)		(0.570)
Disagreement		5.707***		2.959***		2.734***
		(0.357)		(0.184)		(0.172)
MOM-1M		-0.769		-0.579		-0.186
		(0.681)		(0.354)		(0.326)
TURN		30.237***		15.271***		14.906***
		(0.969)		(0.505)		(0.462)
IVOL		2.133***		1.071***		1.062***
		(0.211)		(0.109)		(0.102)
E/P		-3.197***		-1.704***		-1.468***
		(0.376)		(0.196)		(0.179)
BM		0.935***		0.442***		0.493***
		(0.280)		(0.144)		(0.137)
SIZE		-2.300***		-1.302***		-1.001**
		(0.815)		(0.416)		(0.398)
PROF		0.865***		0.479***		0.376**
		(0.319)		(0.164)		(0.154)
INV		-0.649***		-0.327***		-0.320***
		(0.209)		(0.108)		(0.101)
LEV		0.924***		0.459***		0.466***
		(0.305)		(0.157)		(0.147)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	180583	180583	180583	180583	180583	180583
R-sq	0.228	0.351	0.226	0.345	0.231	0.357

Note: This table examine how relative sentiment (Relative Sentiment) affects the retail order flow. Column (1) and (2) we regress total retail order flow (Total Order Flow) on Relative Sentiment while controlling the Own Sentiment. Then additionally control Fraction HOB, Disagreement and other firm controls including past 4-week excess returns exclude the recent week (MOM-1M), the one-week lagged turnover (Lag. Turnover) and last month idiosyncratic volatility (IVOL), earning to price ratio (E/P), book to market ratio (BM), log market capitalization (SIZE), profitability (PROF), investment (INV) and Leverage (LEV). Column (3) to (6) demonstrate the same regression specifications by replacing the dependent variables to Retail Buy Order, Retail Sell Order, respectively. All variables are winsorized at 1% - 99% level and standardized except MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 6: Retail Order Imbalance Heterogeneity

Dep Var:	(1)	(2)	(3)	(4)	(5)	(6)
	Retail Order Imbalance					
Relative Sentiment	0.023***	0.055***	0.035***	0.056***	0.052***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Relative Sentiment x Uncertainty H	-0.148***					
	(0.009)					
Relative Sentiment x RET Volatility H		-0.144***				
		(0.007)				
Relative Sentiment x IVOL H			-0.103***			
			(0.007)			
Relative Sentiment x Retail Trades H				-0.160***		
				(0.008)		
Relative Sentiment x SIZE L					-0.132***	
					(0.008)	
Relative Sentiment x Bid-Ask Spread H						-0.147***
						(0.008)
Uncertainty H	0.248***					
	(0.011)					
RET Volatility H		0.302***				
		(0.012)				
IVOL H			0.017*			
			(0.010)			
Retail Trades H				0.202***		
				(0.015)		
SIZE L					-0.066***	
					(0.022)	
Bid-Ask Spread H						0.281***
						(0.011)
Firm Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	180583	180583	180583	180583	180583	180577
R-sq	0.132	0.135	0.125	0.128	0.125	0.133

Note: This table examines the heterogeneous effect of Relative Sentiment on Retail Order Imbalance. Column (1) interacts Relative Sentiment with HOB Uncertainty H, where HOB Uncertainty is defined as the average uncertainty scores in HOB posts at firm week level, and the indicator corresponds to High HOB Uncertainty. Column (2) interacts Relative Sentiment with Ret Volatility H, where Ret Volatility H corresponds to high Ret Volatility. Column (3) interacts Relative sentiment with IVOL H, where IVOL H corresponds to high IVOL. Column (4), we define Retail Trades H as firms with relatively higher retail trading activity by using the difference between total trading volume and retail total order flow scaled by share outstanding within a given yearwk and interacts Relative Sentiment with Retail Trades H. Column (5) interacts Relative Sentiment with SIZE L, where SIZE L corresponds to small firms. Column (6) interacts Relative Sentiment with Bid-Ask Spread H, where Bid-Ask Spread H corresponds to firms with larger Bid-Ask Spread in a given week. Firm Characteristics Control includes Own Sentiment, Fraction HOB, Disagreement, MOM-M, Lag. Turnover, IVOL, E/P, BM, SIZE, PROF, INV, LEV. All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * p<0.1 **p<0.05 ***p<0.01

Table 7: Future Returns

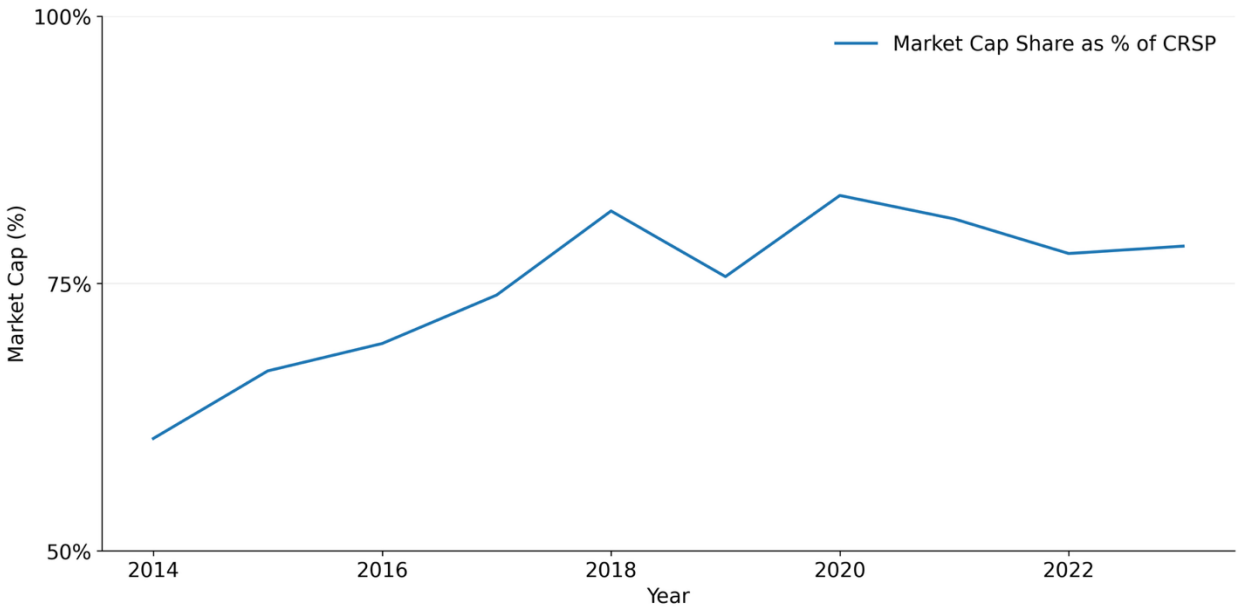
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Panel A: Return in T+1										
		Retail Trades Intensity		RET Volatility		HOB Uncertainty		Size		Bid-Ask Spread	
	All	Low	High	Low	High	Low	High	Low	High	Low	High
Relative Sentiment	0.055***	0.002	0.131***	-0.020	0.151***	0.053***	0.085**	0.080***	0.033**	0.010	0.100***
	(0.016)	(0.018)	(0.035)	(0.016)	(0.031)	(0.018)	(0.036)	(0.030)	(0.016)	(0.016)	(0.031)
Own Sentiment	-0.041**	-0.016	-0.062	-0.022	-0.029	-0.003	-0.073*	-0.071**	-0.008	0.007	-0.125**
	(0.019)	(0.021)	(0.040)	(0.019)	(0.033)	(0.022)	(0.039)	(0.033)	(0.019)	(0.018)	(0.035)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	208172	89705	89340	104070	103346	117787	89723	103818	104081	104110	103358
R-sq	0.142	0.211	0.149	0.190	0.147	0.161	0.155	0.139	0.215	0.200	0.142
	Panel B: Return from T+1 to T+3										
		Retail Trades Intensity		RET Volatility		HOB Uncertainty		Size		Bid-Ask Spread	
	All	Low	High	Low	High	Low	High	Low	High	Low	High
Relative Sentiment	0.119***	0.027	0.230***	0.009	0.249***	0.069**	0.293***	0.165***	0.070**	0.035	0.189***
	(0.029)	(0.031)	(0.065)	(0.029)	(0.056)	(0.032)	(0.067)	(0.053)	(0.028)	(0.028)	(0.057)
Own Sentiment	-0.034	0.003	-0.073	0.013	-0.041	0.021	-0.014	-0.063	-0.013	0.045	-0.167***
	(0.034)	(0.034)	(0.072)	(0.033)	(0.059)	(0.038)	(0.068)	(0.063)	(0.032)	(0.031)	(0.062)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	208172	89705	89340	104070	103346	117787	89723	103818	104081	104110	103358
R-sq	0.187	0.250	0.203	0.220	0.196	0.195	0.213	0.189	0.249	0.229	0.191

Note: This table examines the predictability of Relative Sentiment on future returns. Panel A shows the predictability for RET (T+1). Panel B shows the cumulative returns from T+1 to T+3. We test the same regression specification by regress RET(T+1) or RET(T+1 to T+3) on Relative Sentiment, Own Sentiment, controlling Fraction HOB, disagreement in own sentiment (Disagreement), contemporaneous returns (RET), earnings to price ratio (E/P), book to market (BM), log market capitalization (SIZE)., profitability (PROF), investment (INV), leverage (LEV), as well as one month lagged idiosyncratic volatility (IVOL). Column (1) shows the full sample results. Columns (2) and (3) show the heterogeneity across Retail Trades Intensity. Columns (4) and (5) highlight the heterogeneity across RET Volatility. Columns (6) and (7) demonstrate heterogeneity across HOB uncertainty. Columns (8) and (9) shows the heterogeneity across SIZE. Columns (10) and (11) shows the heterogeneity across Bid-Ask Spread. All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Online Appendix

For Sentiment about Others by Yukun Liu and Xiao Yin

Figure A1: Market Capitalization Coverage as % of CRSP



Note: These figures present the annual market capitalization coverage in our data, expressed as a percentage of CRSP. The sample period spans from 2014 to 2023.

Table A1: Fraction of HOB

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Fraction HOB	<2018	>=2018	<2020	>=2020	<2022	>=2022
Relative Sentiment	0.093	-0.370***	-0.055	-0.394***	-0.215***	-0.273***
	(0.065)	(0.038)	(0.049)	(0.047)	(0.043)	(0.055)
Own Sentiment	0.326***	-0.065	0.241***	-0.044	0.058	0.075
	(0.071)	(0.047)	(0.053)	(0.055)	(0.048)	(0.064)
Disagreement	-0.983***	-0.787***	-1.006***	-0.713***	-0.836***	-0.915***
	(0.062)	(0.046)	(0.052)	(0.053)	(0.045)	(0.067)
RET	-1.640***	-0.795***	-1.233***	-0.982***	-1.048***	-1.338***
	(0.290)	(0.180)	(0.226)	(0.207)	(0.191)	(0.275)
E/P	0.290**	0.257***	0.231**	0.255***	0.259***	0.138
	(0.126)	(0.062)	(0.091)	(0.068)	(0.077)	(0.083)
RET x E/P	-0.164	-0.190**	-0.076	-0.272***	-0.075	-0.363***
	(0.147)	(0.077)	(0.104)	(0.085)	(0.102)	(0.100)
BM	-0.167	0.031	-0.093	0.113	-0.019	0.124
	(0.153)	(0.070)	(0.112)	(0.080)	(0.077)	(0.106)
SIZE	-0.964*	-1.074***	-0.916***	-0.856***	-0.616**	-0.736
	(0.527)	(0.249)	(0.331)	(0.283)	(0.257)	(0.450)
PROF	0.156	0.209***	0.241**	0.160*	0.190**	0.175
	(0.176)	(0.073)	(0.101)	(0.088)	(0.079)	(0.159)
INV	-0.132	-0.073	-0.076	-0.070	-0.137**	-0.058
	(0.108)	(0.046)	(0.090)	(0.048)	(0.059)	(0.063)
LEV	-0.271	-0.078	-0.329***	-0.091	-0.192**	-0.196
	(0.176)	(0.099)	(0.121)	(0.114)	(0.095)	(0.185)
MOM-1M	-0.193	0.445***	0.181	0.338***	0.337***	0.012
	(0.189)	(0.103)	(0.139)	(0.119)	(0.109)	(0.150)
IVOL	-0.656***	-0.506***	-0.656***	-0.467***	-0.623***	-0.381***
	(0.069)	(0.038)	(0.050)	(0.044)	(0.039)	(0.063)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	47452	162292	87164	122565	146402	63326
R-sq	0.236	0.201	0.214	0.212	0.202	0.236

Note: This table examines the fraction of HOB posts (Fraction HOB) relates to higher order belief, first order belief, disagreement measures, and valuation metrics in different subsample. All regressions show the same specification by regress the Fraction HOB on Relative Sentiment, Own Sentiment, disagreement in own sentiment (Disagreement), contemporaneous returns (RET), earnings to price ratio (E/P), interaction variable (RET × E/P), book to market (BM), log market capitalization (SIZE)., profitability (PROF), investment (INV), leverage (LEV), as well as past 4 weeks excess returns exclude the recent 1 week (MOM-1M), and one month lagged idiosyncratic volatility (IVOL). Columns (1) and (2) shows the sample periods before and after 2018. Columns (3) and (4) presents the sample periods before and after 2020. Columns (5) and (6) highlights the sample periods before and after 2022. All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A2: Subjective Sentiment

Dep Var: Subjective Sentiment	(1) <2018	(2) >=2018	(3) <2020	(4) >=2020	(5) <2022	(6) >=2022
Own Sentiment	0.172***	0.200***	0.179***	0.203***	0.179***	0.221***
	(0.008)	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)
Fraction HOB	0.093	-0.290***	-0.051	-0.303***	-0.172***	-0.243***
	(0.064)	(0.029)	(0.045)	(0.035)	(0.034)	(0.049)
Disagreement	-0.647***	-0.679***	-0.672***	-0.666***	-0.709***	-0.578***
	(0.017)	(0.010)	(0.012)	(0.012)	(0.010)	(0.015)
RET	0.068**	0.087***	0.070***	0.096***	0.050***	0.152***
	(0.027)	(0.015)	(0.019)	(0.018)	(0.015)	(0.024)
E/P	-0.006	0.022***	0.015**	0.020***	0.014**	0.020**
	(0.010)	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)
RET x E/P	-0.024	-0.010	-0.008	-0.014	-0.014	-0.001
	(0.018)	(0.008)	(0.012)	(0.009)	(0.011)	(0.009)
BM	0.014	-0.001	0.010	-0.006	0.001	-0.006
	(0.013)	(0.005)	(0.008)	(0.005)	(0.006)	(0.009)
SIZE	-0.005	-0.130***	-0.088***	-0.131***	-0.102***	-0.107***
	(0.041)	(0.017)	(0.028)	(0.022)	(0.018)	(0.036)
PROF	0.017	-0.003	0.006	-0.003	0.006	-0.016
	(0.014)	(0.006)	(0.009)	(0.007)	(0.007)	(0.013)
INV	0.009	-0.004	-0.006	-0.004	-0.005	-0.002
	(0.007)	(0.003)	(0.007)	(0.003)	(0.005)	(0.005)
LEV	-0.006	0.002	-0.009	-0.003	-0.004	-0.016
	(0.016)	(0.006)	(0.010)	(0.007)	(0.007)	(0.014)
MOM-1M	-0.108***	-0.028***	-0.079***	-0.019*	-0.070***	0.004
	(0.018)	(0.009)	(0.014)	(0.011)	(0.011)	(0.013)
IVOL	-0.008	-0.010***	-0.012***	-0.008**	-0.008***	-0.010*
	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	47452	162292	87164	122565	146402	63326
R-sq	0.204	0.195	0.189	0.205	0.188	0.218

Note: This table examines the subjective sentiment (Subjective Sentiment) relates to first order belief, disagreement measures, and valuation metrics in different sample periods. All regressions show the same specification by regress the Subjective Sentiment on Own Sentiment, Fraction HOB, disagreement in own sentiment (Disagreement), contemporaneous returns (RET), earnings to price ratio (E/P), interaction variable (RET × E/P), book to market (BM), log market capitalization (SIZE)., profitability (PROF), investment (INV), leverage (LEV), as well as past 4 weeks excess returns exclude the recent 1 week (MOM-1M), and one month lagged idiosyncratic volatility (IVOL). Columns (1) and (2) shows the sample periods before and after 2018. Columns (3) and (4) presents the sample periods before and after 2020. Columns (5) and (6) highlights the sample periods before and after 2022. All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A3: Retail Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Retail Order Imbalance	<2018	>=2018	<2020	>=2020	<2022	>=2022
Relative Sentiment	-0.022**	-0.012***	-0.010**	-0.012***	-0.011***	-0.015**
	(0.009)	(0.003)	(0.005)	(0.004)	(0.004)	(0.006)
Own Sentiment	0.079***	0.137***	0.102***	0.149***	0.119***	0.157***
	(0.012)	(0.007)	(0.008)	(0.008)	(0.007)	(0.010)
Fraction HOB	-0.317***	-0.681***	-0.449***	-0.768***	-0.452***	-1.187***
	(0.077)	(0.043)	(0.050)	(0.053)	(0.035)	(0.080)
Disagreement	0.177***	0.178***	0.172***	0.182***	0.194***	0.135***
	(0.025)	(0.013)	(0.016)	(0.016)	(0.014)	(0.019)
MOM-1M	-0.380***	-0.334***	-0.262***	-0.349***	-0.243***	-0.473***
	(0.097)	(0.039)	(0.053)	(0.044)	(0.043)	(0.053)
TURN	0.263**	0.309***	0.433***	0.257***	0.373***	0.116
	(0.121)	(0.043)	(0.068)	(0.046)	(0.043)	(0.074)
IVOL	-0.004	0.015	-0.006	0.020*	0.018	-0.005
	(0.022)	(0.010)	(0.014)	(0.011)	(0.011)	(0.015)
E/P	-0.520***	-0.152***	-0.272***	-0.133***	-0.187***	-0.148***
	(0.120)	(0.020)	(0.045)	(0.021)	(0.032)	(0.029)
BM	-0.023	-0.052***	-0.026	-0.052***	-0.053***	-0.044**
	(0.044)	(0.013)	(0.028)	(0.015)	(0.015)	(0.021)
SIZE	0.739**	-0.316***	-0.105	-0.358***	-0.243***	-0.311***
	(0.309)	(0.038)	(0.083)	(0.047)	(0.044)	(0.084)
PROF	0.094*	0.057***	0.073***	0.061***	0.060***	0.074*
	(0.051)	(0.016)	(0.024)	(0.022)	(0.017)	(0.041)
INV	0.019	-0.004	-0.005	-0.010	-0.017*	-0.010
	(0.034)	(0.009)	(0.021)	(0.010)	(0.010)	(0.015)
LEV	-0.087	-0.015	-0.004	-0.016	-0.002	-0.054
	(0.064)	(0.013)	(0.020)	(0.018)	(0.014)	(0.033)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18475	162292	58141	122565	117374	63326
R-sq	0.197	0.125	0.148	0.128	0.110	0.182

Note: This table examines the retail order imbalance (Retail Order Imbalance) relates to Relative sentiment in different sample periods. All regressions show the same specification by regress the Retail Order Imbalance on Relative Sentiment, Own Sentiment, Fraction HOB, disagreement in own sentiment (Disagreement), past 4 weeks excess returns exclude the recent 1 week (MOM-1M), last week turnover (TURN) and one month lagged idiosyncratic volatility (IVOL), as well as firm characteristics including earnings to price ratio (E/P), book to market (BM), log market capitalization (SIZE)., profitability (PROF), investment (INV), leverage (LEV)Columns (1) and (2) shows the sample periods before and after 2018. Columns (3) and (4) presents the sample periods before and after 2020. Columns (5) and (6) highlights the sample periods before and after 2022. All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A4: Retail Order and Subjective Sentiment

Dep Var:	(1) Retail Order Imbalance	(2) Total Retail Order	(3) Retail Buy Order	(4) Retail Sell Order
Subjective Sentiment	-0.009***	-0.334***	-0.172***	-0.162***
	(0.003)	(0.055)	(0.028)	(0.026)
Objective Sentiment	0.141***	4.272***	2.218***	2.046***
	(0.006)	(0.202)	(0.104)	(0.097)
Fraction HOB	-0.643***	-17.526***	-9.125***	-8.383***
	(0.040)	(1.184)	(0.611)	(0.570)
Disagreement	0.174***	5.707***	2.959***	2.734***
	(0.012)	(0.357)	(0.184)	(0.172)
MOM-1M	-0.343***	-0.769	-0.579	-0.186
	(0.036)	(0.681)	(0.354)	(0.326)
TURN	0.318***	30.237***	15.271***	14.906***
	(0.042)	(0.969)	(0.505)	(0.462)
IVOL	0.016*	2.133***	1.071***	1.062***
	(0.009)	(0.211)	(0.109)	(0.102)
E/P	-0.160***	-3.197***	-1.704***	-1.468***
	(0.020)	(0.376)	(0.196)	(0.179)
BM	-0.051***	0.935***	0.442***	0.493***
	(0.012)	(0.280)	(0.144)	(0.137)
SIZE	-0.275***	-2.300***	-1.302***	-1.001**
	(0.035)	(0.815)	(0.416)	(0.398)
PROF	0.062***	0.865***	0.479***	0.376**
	(0.015)	(0.319)	(0.164)	(0.154)
INV	-0.004	-0.649***	-0.327***	-0.320***
	(0.009)	(0.209)	(0.108)	(0.101)
LEV	-0.012	0.924***	0.459***	0.466***
	(0.012)	(0.305)	(0.157)	(0.147)
Firm FE	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes
N	180583	180583	180583	180583
R-sq	0.123	0.351	0.345	0.357

Note: This table examine how subjective sentiment (Subjective Sentiment) affects the retail order flow. Column (1) we regress total retail order flow imbalance (Retail Order Imbalance) on Subjective Sentiment while controlling the Own Sentiment controlling Fraction HOB, Disagreement and other firm controls including past 4-week excess returns exclude the recent week (MOM-1M), the one-week lagged turnover (Lag. Turnover) and last month idiosyncratic volatility (IVOL), earning to price ratio (E/P), book to market ratio (BM), log market capitalization (SIZE), profitability (PROF), investment (INV) and Leverage (LEV). Column (2) to (4) demonstrate the same regression specifications by replacing the dependent variables to Total Retail Order, Retail Buy Order, Retail Sell Order, respectively. All variables are winsorized at 1% - 99% level and standardized except MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A5: Robustness for Fixed Effect and Clusters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep Var:	Fraction Hob			Subjective Sentiment			Retail Order Imbalance		
Relative Sentiment							-0.009***	-0.008**	-0.008*
							(0.003)	(0.003)	(0.004)
Subjective Sentiment	-0.233***	-0.250***	-0.250***						
	(0.033)	(0.037)	(0.023)						
Objective Sentiment	-0.524***	-0.524***	-0.524***	0.198***	0.198***	0.198***	0.114***	0.114***	0.114***
	(0.038)	(0.039)	(0.023)	(0.005)	(0.005)	(0.002)	(0.006)	(0.006)	(0.004)
Objective Disagreement	-1.255***	-1.212***	-1.212***	-0.729***	-0.736***	-0.736***	0.182***	0.171***	0.171***
	(0.050)	(0.052)	(0.024)	(0.009)	(0.008)	(0.006)	(0.012)	(0.012)	(0.009)
Fraction HOB				-0.208***	-0.220***	-0.220***	-0.497***	-0.500***	-0.500***
				(0.030)	(0.033)	(0.021)	(0.036)	(0.036)	(0.032)
RET	-0.164	-0.014	-0.014	0.059***	0.082***	0.082***			
	(0.163)	(0.191)	(0.149)	(0.013)	(0.013)	(0.014)			
E/P	0.357***	0.234***	0.234***	0.002	0.006	0.006**	-0.162***	-0.162***	-0.162***
	(0.056)	(0.060)	(0.028)	(0.004)	(0.004)	(0.003)	(0.016)	(0.016)	(0.004)
RET x E/P	0.068	0.081	0.081	-0.020***	-0.014**	-0.014			
	(0.073)	(0.077)	(0.092)	(0.007)	(0.007)	(0.009)			
BM	-0.087	0.013	0.013	0.001	0.002	0.002	-0.033***	-0.037***	-0.037***
	(0.063)	(0.065)	(0.024)	(0.004)	(0.003)	(0.002)	(0.008)	(0.008)	(0.003)
SIZE	-1.495***	-1.422***	-1.422***	-0.037***	-0.036***	-0.036***	-0.141***	-0.142***	-0.142***
	(0.118)	(0.121)	(0.032)	(0.006)	(0.006)	(0.003)	(0.010)	(0.010)	(0.005)
PROF	0.841***	0.863***	0.863***	0.010***	0.010**	0.010***	0.030***	0.032***	0.032***
	(0.063)	(0.064)	(0.028)	(0.004)	(0.004)	(0.003)	(0.008)	(0.008)	(0.004)
INV	-0.276***	-0.217***	-0.217***	-0.005*	-0.009***	-0.009***	-0.002	0.002	0.002
	(0.044)	(0.045)	(0.023)	(0.003)	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)
LEV	0.130*	0.141*	0.141***	0.000	0.000	0.000	0.004	0.004	0.004
	(0.076)	(0.078)	(0.023)	(0.004)	(0.004)	(0.002)	(0.006)	(0.006)	(0.003)
MOM-1M	0.668***	0.438***	0.438***	-0.061***	-0.041***	-0.041***	-0.425***	-0.341***	-0.341***
	(0.102)	(0.123)	(0.081)	(0.008)	(0.008)	(0.008)	(0.037)	(0.036)	(0.012)
IVOL	-0.788***	-0.698***	-0.698***	-0.010***	-0.009***	-0.009***	0.021**	0.030***	0.030***
	(0.040)	(0.043)	(0.026)	(0.003)	(0.003)	(0.002)	(0.008)	(0.009)	(0.004)
TURN							0.429***	0.431***	0.431***
							(0.042)	(0.042)	(0.009)
Firm FE	No	No	No	No	No	No	No	No	No
Yearwk FE	Yes	No	No	Yes	No	No	Yes	No	No
Cluster Yearwk & Firm	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
N	210645	210645	210645	210645	210645	210645	181561	181561	181561
R-sq	0.051	0.032	0.032	0.145	0.140	0.140	0.092	0.082	0.082

Note: This table reports robustness checks with different specifications of fixed effects and clustering. In columns (1) to (3), we replicate the regression specification in column (6) of Table 2 while varying the fixed effects and clustering schemes. Columns (4) to (6) apply the same set of specifications to Subjective Sentiment as the dependent variable. Columns (7) to (9) repeat the analysis using Retail Order Imbalance as the dependent variable. Control variables include Own Sentiment controlling Fraction HOB, Disagreement and other firm controls including past 4-week excess returns exclude the recent week (MOM-1M), the one-week lagged turnover (Lag. Turnover) and last month idiosyncratic volatility (IVOL), earning to price ratio (E/P), book to market ratio (BM), log market capitalization (SIZE), profitability (PROF), investment (INV) and Leverage (LEV). For Columns (1) to (6), we additionally include the interaction term between RET and E/P. All variables are winsorized at 1% - 99% level and standardized except MOM-1M. * p<0.1, ** p<0.05, *** p<0.01

Table A.6: Fama Macbeth Regression

	(1)	(2)	(3)	(4)	(5)
Dep Var:			RET (T+1)		
Relative Sentiment	0.081***	0.033**	0.025**	0.025**	0.034***
	(0.010)	(0.013)	(0.013)	(0.012)	(0.012)
Own Sentiment		-0.099***	-0.107***	-0.076***	-0.055***
		(0.021)	(0.020)	(0.019)	(0.019)
Fraction HOB			0.112	-0.014	0.095
			(0.155)	(0.147)	(0.145)
Disagreement			-0.078	-0.107**	-0.221***
			(0.048)	(0.046)	(0.042)
MOM-1M				-0.200	-0.439***
				(0.126)	(0.108)
lag. TURN				-0.059	-0.112
				(0.124)	(0.115)
IVOL				-0.294***	-0.079**
				(0.033)	(0.031)
E/P					0.087
					(0.057)
BM					-0.044
					(0.034)
PROF					0.138***
					(0.029)
INV					-0.063**
					(0.027)
LEV					-0.048**
					(0.021)
SIZE					0.277***
					(0.036)
R-sq	0.004	0.008	0.015	0.052	0.104
Avg. # Firms	384	384	384	384	384
# Weeks	543	543	543	543	543

Note: This table examines the return predictability of Relative Sentiment using Fama-Macbeth regressions. We evaluate whether Relative Sentiment predicts next week firm returns (RET (T+1)). The dependent variable is the annualized log excess returns in week T+1. Column (1) reports a univariate Fama-Macbeth regression of RET(T+1) on Relative Sentiment at week T. Column (2) to (3) further control the Own Sentiment, Fraction HOB and Disagreement, respectively. Column (4) further includes past 4-week excess returns exclude the recent week (MOM-1M), the one-week lagged turnover (Lag. Turnover) and last month idiosyncratic volatility (IVOL). Column (5) we additionally control for firm characteristics, including earning to price ratio (E/P), book to market ratio (BM), log market capitalization (SIZE), profitability (PROF), investment (INV) and Leverage (LEV). All variables are winsorized at 1% - 99% level and standardized except RET and MOM-1M. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$