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 first-order and higher-order sentiment. We find that references to others are pervasive and mostly optimistic. Retail order imbalance increases with first-order sentiment but decreases with higher-order sentiment. Higher-order sentiment also positively predicts short-horizon returns, especially where contrarian retail trading is strongest.

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I. Introduction

In the stock market, 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 strategic behavior unfolds and are important for determining price dynamics.

Classic theories in finance emphasize that beliefs about others are central to price formation and speculative trading.[1] Yet, despite the importance of higher order reasoning, direct empirical evidence on investors' beliefs of others remains scarce, especially at the firm level. 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' perception of others' sentiment relates to market activities. In particular, we focus on the social media investing platform StockTwits, where users often express verbal description regarding specific securities. 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 or beliefs of other investors.

Traditional lexicon-based sentiment tools cannot make this distinction because they capture polarity and are incapable of distinguishing between topics that mostly use the same words. Modern language models can perform context related reasoning. This 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 thoughts or describing the reasoning or expected actions of other investors. Messages referencing others yield our initial selection of HOB messages. However, references to others can take different temporal forms: investors may rationalize others' past behavior,

[1] See Allen et al. (2006), Bacchetta and van Wincoop (2006, 2008), Banerjee et al. (2009), Kasa et al. (2014), Cespa and Vives (2015), Nimark (2017), and Schmidt-Engelbertz and Vasudevan (2023) for examples.

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 to focus on those that explicitly refer to others' expectations or actions in the future, excluding messages that merely rationalize past outcomes or describe contemporaneous conditions.

For each higher-order message, we extract the sentiment of the message content, which provides a measure of *higher-order 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 *first-order sentiment*. Then we aggregate the sentiment measure for each firm and week. Our final sample is a panel of weekly first-order and higher-order sentiment measure covering 4,314 firms over 551 weeks from 2014 to 2024.

We provide several validation exercises to assess the credibility of our sentiment measures. First, we show that HOB posts and first-order-belief (FOB) posts rely on largely overlapping vocabularies, but that HOB posts feature substantially more language referring to other investors, groups, and their expected actions. Second, because an LLM could in principle encode a notion of HOB that differs from how human readers ordinarily interpret such references, misclassification would therefore arise. We then verify that the LLM applies a coherent, common-sense understanding of HOB. Third, we validate our classification against an alternative language model (GPT-5 mini) and independent human hand-coding, achieving roughly 80% agreement in both cases. Finally, we benchmark our higher-order sentiment measure against the perceived sentiment of other investors from Robert Shiller's Investor Confidence Surveys and find a highly significant positive relationship, indicating that our measure aligns with established survey-based indicators of investors' beliefs about others.

The data reveal several notable patterns of HOB posting and higher-order sentiment. References to others' reasoning are common, with roughly one-third of messages describing what other agents think or are expected to do, a share that remains stable over time. The fraction of higher-order posting varies systematically with investors' own beliefs

and the information environment. Investors talk more about others when they are optimistic themselves but perceive others as more pessimistic, and higher-order posting also rises following low returns. Beyond posting volume, higher-order sentiment itself responds to market conditions, becoming more sensitive to return movements when valuation is high, which suggests that the beliefs investors attribute to others depend jointly on prices and their alignment with fundamentals. Together, these patterns show that perceptions of others' expectations reflect not only one's own beliefs but also the broader informational environment.

We next examine retail order flow to assess how our sentiment measures relate to actual trading behavior.[2] We find that retail buying increases with first-order sentiment. However, after controlling for first-order sentiment, trading patterns display a net-selling association to beliefs about others: more optimistic perception of others is associated with more retail net selling. Average magnitudes are statistically significant but, nonetheless, small in magnitude: a one-standard-deviation increase in higher-order sentiment shifts retail order imbalance up by only about 0.008 standard deviations, or 0.026 of its interquartile range. (IQR).

While the average relationship between higher-order sentiment and retail trading is economically modest, there is substantial heterogeneity across stock characteristics. We find that the association between retail order imbalance and higher-order sentiment becomes an order of magnitude larger when retail activities are more active, when uncertainty is high, or when the stocks are more illiquid: in these environments, the same increase in higher-order sentiment is associated with an around 0.10-standard-deviation increase in retail net selling. These patterns suggest that investors' net selling trading behaviors depends on the broader market environment.

We then turn to the implications of higher-order sentiment for return dynamics.

[2] 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. However, 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).

Here, higher-order and first-order sentiment display sharply different predictive patterns. First, both higher-order sentiment and first-order 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 first-order sentiment predicts a 4.1% lower annualized return in the following week. In contrast, higher-order sentiment positively predicts future returns. A one-standard deviation increase in higher-order 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.

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 et al. 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 (2026) document contrarian responses to beliefs about others using randomized belief variation. While previous empirical works have largely focused on the market level, 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 subjectively think others disagree. We contribute by constructing a firm-level, high-frequency measure of subjective disagreement, which is the difference between first-order sentiment and subjective perception of the sentiment of others, providing a new dimension of belief heterogeneity that can be linked to trading behavior.

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).

More recently, large language models have been applied to a range of economic and financial questions, including extracting forward-looking corporate policies from conference calls (Jha et al., 2024), analyzing sentiment in news headlines and asset-price predictability (Lopez-Lira and Tang, 2023), parsing central-bank communication (Hansen and Kazinnik, 2023), identifying redundant or low-information disclosures (Kim, Muhn, and Nikolaev, 2023), forecasting innovation outcomes (Yang, 2023), studying disclosure behavior in the presence of AI listeners (Cao et al., 2023), dissecting corporate culture (Li et al., 2026), and studying the emergence of investor disagreement (Bhagwat et al., 2026). These advances demonstrate that LLMs can recover complex, economically meaningful objects that were previously difficult to measure using traditional NLP tools. 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 sentiment about others to firm-level trading behavior in real time.

The remainder of this paper is organized as follows: Section II lays out a simple model to build intuition. Section III describe the data. Section IV discuss the higher-order sentiment measurement. Section V studies the fraction of HOB posts and higher-order sentiment. Section VI document the relationship between higher-order sentiment of trading activities and return dynamics. Section VII concludes the paper.

II. Model

In this section, we present a simple model to illustrate the relationship between HOB, trading decisions, and price dynamics. The model builds on Allen et al. (2006) and is stylized to build intuition.

A. Environment

There are three dates $t \in \{0,1,2\}$. A single risky asset is traded at $t = 0, 1$ and pays a terminal payoff $v \sim N(0, \sigma_v^2)$ at $t = 2$. Asset supply at date t is $Q_t \sim N(0, \sigma_Q^2)$, independent of all other shocks. There is a continuum of investors with unit mass, divided into two types: a fraction $\phi \in (0, 1)$ are institutional investors and the remaining $1 - \phi$ are retail investors. Both types are myopic. At date t, investor i chooses position $x_{i,t}$ to maximize

$$x_{i,t}\left(\hat{E}_{i,t}[V_{t+1}] - p_t\right) - \frac{x_{i,t}^2}{2\chi},$$

where $\hat{E}_{i,t}[V_{t+1}]$ is investor i's subjective expectation of next period payoff V_{t+1}. $V_2 = v$ and $V_1 = p_1$. $\chi > 0$ captures the risk tolerance. The first-order condition implies linear demand

$$x_{i,t} = \chi\left(\hat{E}_{i,t}[V_{t+1}] - p_t\right). \quad (1)$$

B. Optimality Condition in Date 1

1. Information Structure

We solve the model by backward induction. Date-1 investors hold heterogeneous prior beliefs about the terminal payoff. Each investor *j* enters date 1 with prior $v \sim N(\theta_j, \sigma_v^2)$, where

$$\theta_j = \theta + \eta_j, \qquad \theta \sim N(0, \sigma_\theta^2), \qquad \eta_j \sim N(0, \sigma_\eta^2).$$

The common component $\theta = \int \theta_j dj$ is the cross-sectional average prior, which captures the prevailing consensus view about v. Each investor regards θ_j as the correct prior mean and understands that others hold different views, generating persistent *agreeing-to-disagree* a la Harrison and Raviv (1993), Scheinkman and Xiong (2003), and Caballero and Simsek (2021).

At date 1, each investor additionally observes a private signal $s_{j,1} = v + \varepsilon_{j,1}$, with $\varepsilon_{j,1} \sim N(0, \sigma_\varepsilon^2)$. Bayesian updating yields

$$\hat{E}_j[v \mid s_{j,1}] = (1 - \kappa_\theta) s_{j,1} + \kappa_\theta \theta_j,$$

where $\kappa_\theta = \sigma_\varepsilon^2/(\sigma_v^2 + \sigma_\varepsilon^2)$. The weight κ_θ measures the dogmatism of the investor population. Aggregating across the continuum,

$$m_1 \equiv \int \hat{E}_j[v \mid s_{j,1}] dj = (1 - \kappa_\theta) v + \kappa_\theta \theta. \tag{2}$$

2. Optimality Conditions

At date 1, investor *j*'s demand follows from (1)

$$x_{j,1} = \chi\left(\hat{E}_{j,1}[V_{t+1}] - p_t\right) = \chi\left((1 - \kappa_\theta) s_{j,1} + \kappa_\theta \theta_j - p_1\right)$$

Aggregating across investors gives $\int x_{i,1} dj = \chi(m_1 - p_1)$. Market clearing $\int x_{i,1} dj =$ gives

$$p_1 = m_1 - \frac{Q_1}{\chi} = (1 - \kappa_\theta) v + \kappa_\theta \theta - \frac{Q_1}{\chi} \tag{3}$$

3. Higher-order beliefs

The dependence of $\boldsymbol{p_1}$ on $\boldsymbol{m_1}$ implies that date-0 investors must forecast the average future belief. Following Allen et al. (2006), define investor $\boldsymbol{j}$'s higher-order belief in date-0 as

$HOB_{j,0} = E_{j,0}[m_1] = (1-\kappa_\theta)E_{j,0}[v] + \kappa_\theta E_{j,0}[\theta]$. The first term reflects first-order beliefs about fundamentals, while the second term captures expectations of the non-fundamental valuation. Therefore, controlling for FOB, HOB reflects subjective expectation of the non-fundamental valuation (i.e., sentiment) in the market, similar to that in Gorodnichenko and Yin (2026).

To isolate the non-fundamental variation, define the residualized aggregate higher-order belief $B_0 \equiv \kappa_\theta \theta$, which is the average HOB residualized by FOB. Since $v \perp \theta$, B_0 is orthogonal to first-order beliefs and captures the component of expected resale value driven by the consensus interpretation.

C. Optimality Condition in Date 0

1. Information Structure

At $t = 0$, investor j observes a private signal $s_{j,0}$ about fundamentals, forming the posterior mean $\mu_{j,0} \equiv \hat{E}_j[v \mid s_{j,0}]$. This signal is uninformative about θ. In addition, each investor in group $k \in \{H, L\}$ receives a private signal about the higher-order component,

$$B_j = B_0 + \xi_i, \qquad \xi_j \sim N(0, \sigma^2_{\xi,k}),$$

with idiosyncratic signal noise independent across investors and independent of all other shocks. Institutional traders and retail traders differ in signal precision. Let

$$\omega_k \equiv \frac{\sigma_B^2}{\sigma_B^2 + \sigma^2_{\xi,k}}, \qquad k \in \{H, L\},$$

and assume $0 < \omega_L < \omega_H < 1$. That is, institutional traders have high precision ω_H, while retail traders have low precision ω_L. Both types also observe the equilibrium price, which provides an additional public signal about B_0.

2. Optimality Conditions

At date 0, investors trade for resale. Since $V_1 = p_1$, the date-0 demand of investor j in group $k \in \{H, L\}$ satisfies

$$x^k_{j,0} = \chi\left(\hat{E}^k_{j,0}[p_1] - p_0\right) \tag{4}$$

From equation (3) and market-clearing condition,

$$\hat{E}^k_{j,0}[p_1] = (1-\kappa_\theta)\mu_{j,0} + \hat{E}^k_{j,0}[\theta]. \tag{5}$$

Thus date-0 demand depends on first-order beliefs about fundamentals, s_0, and on beliefs about the higher-order component, $\hat{E}^k_{j,0}[\theta]$.

Denote $v_0 = (1-\kappa_\theta)v$, we conjecture a linear equilibrium price

$$p_0 = v_0 + lB_0 - \rho Q_0, \tag{6}$$

where l measures how aggressively the market capitalizes higher-order beliefs. Investors extract a normalized price signal

$$s_p \equiv \frac{p_0 - \beta_\mu \mu_0}{l} = B_0 - \frac{\rho}{l} Q_0.$$

Each group $k \in \{H, L\}$ combines its private signal B_i and the price signal s_p. Standard Gaussian updating yields

$$\hat{E}_j\left[B_0 \mid B_j, s_p\right] = \alpha_k B_j + \psi_k s_p,$$

where $\alpha_k = \frac{\omega_k(1-\gamma)}{1-\omega_k\gamma}$, $\psi_k = \frac{\gamma(1-\omega_k)}{1-\omega_k\gamma}$, and $\gamma = \frac{l^2\sigma_B^2}{l^2\sigma_B^2+\rho^2\sigma_Q^2}$. The total loading of group k on B_0 is then $A_k \equiv \alpha_k + \psi_k = \frac{\omega_k+\gamma-2\omega_k\gamma}{1-\omega_k\gamma}$.

Substituting (5) and (6) into (4) and aggregating within each group gives

$$X^H = \phi\chi\left[(1-\kappa_\theta)(\lambda_s - 1)v + (A_H - l)B_0 + \rho\left(1 - \frac{\psi_H}{l}\right)Q_0\right],$$

$$X^L = (1-\phi)\chi\left[(1-\kappa_\theta)(\lambda_s - 1)v + (A_L - l)B_0 + \rho\left(1 - \frac{\psi_L}{l}\right)Q_0\right]. \tag{7}$$

Equation (7) gives the following Lemma

Lemma 1. There exists a unique linear equilibrium of the form (6) with $0 < A_L < l < A_H < 1$.

The key object is the ordering $A_L < l < A_H < 1$: upon receiving a signal about B_0, both retail and institutional traders only incorporate a fraction of the information due to noise in the signals, rendering both A_L and A_H less than one. Meanwhile, retail traders are more

uncertain, therefore $A_L < A_H$. Given price aggregates expectations in the market, it moves more with B_0 than retail's belief but less than institution's belief. In the end, $A_L < l < A_H$.

D. Main Predictions

The ordering $0 < A_L < l < A_H < 1$ from Lemma 1 generates the following five testable predictions.

Proposition 1. Higher residualized HOB is associated with higher contemporaneous prices, i.e., $\partial \hat{E}[\, p_0 \mid B_0, \mu_0\,]/\partial B_0 = l > 0$.

Proposition 2. Retail and institutional order flows respond to B_0 *in opposite directions:*

$$\frac{\partial \hat{E}[X^L \mid B_0, \mu_0]}{\partial B_0} = (1-\phi)\chi(A_L - l) < 0; \quad \frac{\partial \hat{E}[X^H \mid B_0, \mu_0]}{\partial B_0} = \phi\chi(A_H - l) > 0.$$

Proposition 3. Let $r_1 \equiv p_1 - p_0$. *Then* $\partial \hat{E}[\, r_1 \mid B_0, \mu_0\,]/\partial B_0 = 1 - l > 0$.

Proposition 4: The magnitude of retail contrarian trading is decreasing in retail signal precision, i.e., $\partial(l - A_L)/\partial \omega_L < 0$.

Proposition 5. Return continuation is increasing in retail share: $\partial(1-l)/\partial(1-\phi) > 0$.

The intuition behind the five propositions is as follows. When $B_0 > 0$, both types revise upward their expectations of the date-1 consensus non-fundamental valuation, raising the expected resale value. Because institutional signals are more precise, institutions place a higher weight on B_0, captured by $A_H > A_L$, and increase demand more. Market clearing implies that the date-0 price loads on B_0 with coefficient $l = \phi A_H + (1-\phi)A_L$, a population-weighted average of the two groups' responses. Since $A_L < l < A_H$, the price reflects more of B_0 than retail's own posterior valuation but less than institutions' posterior valuation. As a result, through the HOB dimension, the price exceeds retail's valuation, inducing retail to sell, while remaining below institutions' valuation, inducing institutions to buy. The two groups therefore trade against each other, with retail absorbing institutional demand.

Because $l < 1$, the price does not fully incorporate the forecasting power of B_0 for future valuation. The residual component $(1-l)B_0$ is realized at date 1 when the consensus component materializes, generating predictable returns.

The strength of this mechanism is governed by the information structure. A larger precision gap $\omega_H - \omega_L$ increases the dispersion in responses, $A_H - A_L$, raising the wedge between price and retail valuation and inducing more selling by retail. A higher institutional share ϕ shifts the population average l toward A_H, amplifying the price response to the higher-order component.

III. 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, using "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[3].

IV. 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 understanding 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,

[3] See Yin and Zou (2026) for a detailed description and validation of the data.

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.

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 HOB as illustrated in Section II 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 HOB 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 analyze the 17,941,612 Gemini-classified HOB messages using these prompts and classify each HOB message to whether they refer to "Past", "Present" or "Future". In the end, the fractions are 32.5%, 40%, and 27.5%, respectively. Motivated by this distribution, we subsequently redefine expectation-forming HOB messages as those that describe other's future beliefs, which more closely align with the conceptual definition of higher-order-belief. Overall, StockTwtis messages that express beliefs about other's future beliefs or actions represent about 12.59% of total messages in our sample.

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.*

C. Measuring Sentiment

We next use Gemini to extract a sentiment score from each HOB message. 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 *Higher-order 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 *First-order 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 *Higher-order Sentiment* and the average *First-order Sentiment* to get the firm-week level measure. To ensure that our analysis focus on the same sample, we remove observations with no HOB messages. The resulting panel contains 210,561 firm-week observations, covering a total of 4,314 unique firm over 551 weeks from January 2014 to July 2024. Each week, there are roughly 381 firms.[4]

[4] 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.

In the end, to easily track whether investors think others are becoming more or less optimistic relative to themselves, we construct *Relative Sentiment* as the difference between standardized higher-order sentiment and standardized first-order sentiment.[5] In all regressions involving *Relative Sentiment*, we control directly for standardized first-order sentiment, so the coefficient on relative sentiment captures the incremental association of higher-order sentiment.

Note that first-order sentiment is measured from users' bullish/bearish tags, while higher-order sentiment is extracted from message content about others' expected beliefs or actions; these objects may differ in source, wording, and horizon. The intended empirical object is therefore sentiment attributed to others after accounting for first-order sentiment. This maps to the model's residualized HOB term: conditional on FOB, HOB captures the subjective expectation of the non-fundamental resale-value component. Because first-order tags need not be pure measures of fundamentals, we interpret *Relative Sentiment* as a perceived-belief wedge.

D. Some Basic Patterns

We begin by documenting the linguistic features that distinguish HOB posts from FOB posts. Figure 2 presents word clouds constructed from FOB messages (Panel A), HOB messages (Panel B), and the difference in word usage between the two (Panel C).

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*. This overlap indicates that both types of posts revolve around the same underlying investment themes, including predicting price movements, describing trading actions, and interpreting market conditions.

Second, the broad similarity of the two word clouds confirms that HOB and FOB posts do not rely on distinct vocabularies. This is expected, as both types of messages often concern beliefs about future market outcomes. Importantly, this similarity illustrates why simple lexicon-based NLP approaches are ill-suited for identifying HOB content: because

[5] Online Appendix Table A.4 shows that using *Higher-order Sentiment* instead do not change the results.

FOB and HOB posts use largely the same words, distinguishing them requires contextual language understanding rather than differences in word frequency alone.

Third, Panel C isolates words that appear disproportionately more often in HOB posts relative to FOB posts. These include terms such as *people*, *everyone*, *bears*, *shorts*, and *think*, which explicitly reference other investors or groups and align closely with the conceptual definition of HOB as beliefs about others' beliefs or actions.

Finally, Panel D contrasts posts referring primarily to future outcomes with those referring to current or past conditions. Words such as *will*, *going*, and *soon* appear more frequently in forward-looking messages, consistent with the notion that higher-order belief expressions often involve anticipation of how others will react in future market states. 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 12% 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 shows the evolution of higher-order and first-order sentiment. Panel A shows that both measures are predominantly positive over the sample period. Both sentiment series exhibit substantial time-series variation, suggesting that neither first-order nor higher-order beliefs remain anchored around a fixed level. From Panel B, relative sentiment fluctuates widely across the sample. For example, during the onset of COVID, higher-order sentiment fell much more sharply than first-order sentiment, indicating that

investors perceived others as especially pessimistic early in the pandemic. During the rebound in late 2020, higher-order sentiment rose more quickly than first-order sentiment, suggesting that investors viewed others as becoming unusually optimistic relative to their own stated beliefs.

E. Validating the Measure

It is important to verify that the LLM is performing the intended task in our setting, where FOB and HOB posts rely on largely overlapping vocabularies. In this section, we provide additional validation of our approach.

An important preliminary step is to ensure that the LLM applies a coherent, common-sense understanding of HOB. Otherwise, the model may classify posts as higher-order based on reasoning that deviates from that of human. To assess this, we directly query Gemini to 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 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 HOB. 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.

Second, we benchmark our sentiment measures against an established survey-based approach to investor beliefs. In particular, 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 higher-order sentiment as the weekly 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 first-order sentiment as the four 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, 3 months, 6 months, and 12 months?

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 higher-order sentiment on the four first-order sentiment measures.

Figure 6 plots the relative sentiment measure constructed from the Shiller survey against our corresponding measure. Given differences in question framing and the underlying investor samples, large discrepancy between the two series is 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 0.208-standard-deviation increase in the Shiller relative sentiment, with a *t*-statistic of 3.15. 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.[6]

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, higher-order and first-order sentiment 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.

F. 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'

[6] In Online Appendix Figure A.2, we show that the relationship holds both before and after 2020.

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. *First-order Sentiment*, based on users' self-reported bullish or bearish tags, is positive on average (0.299) with a standard deviation of 0.488, suggesting that users tend to express more optimistic views. *Higher-order 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.

V. Stylized Pattern of Higher-order Sentiment

A. Fraction of HOB Posts

We first ask the question: when are investors more likely to express their thoughts about others? 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 *Higher-order Sentiment* is associated with roughly a 0.20 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.

Second, the fraction of HOB posts is higher when contemporaneous returns are low or 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 0.25 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. Higher-order Sentiment

We next study how *Higher-order Sentiment* co-moves with firm characteristics when controlling for investors' *First-order Sentiment*. Table 3 regress *Higher-order Sentiment* on the same set of firm characteristics and fixed effects in Table 2. Across all specifications, *Higher-order Sentiment* is positively associated with *First-order Sentiment*: a one-standard-deviation increase in *First-order Sentiment* corresponds to roughly a 0.195-standard-deviation increase in *Higher-order Sentiment*, consistent with the time-series co-movement in Figure 5. However, *Higher-order 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.

Higher-order 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 (2026), 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, higher-order sentiment is also higher when contemporaneous returns are high and when E/P is high: from column (4), a 10% higher return is associated with roughly a 0.009-standard deviation higher *Higher-order Sentiment*, and a one-standard-deviation higher E/P is associated with roughly a 0.02-standard deviation higher *Higher-order Sentiment*. Therefore, investors tend to believe that others are more optimistic when return is higher or fundamental is strong.

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. *Higher-order 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: the fraction of HOB posts increases when return is low or E/P is high, while *Higher-order Sentiment* becomes more positive when both return and E/P are higher.

VI. Higher-order Sentiment and Market Activities

A. Retail Trading Activities

How investors trade in response to their beliefs about others has long been discussed. Investors may follow others' expected actions when they view those beliefs as informative about fundamentals, generating a momentum-style response (Hong and Stein 1999; Bikhchandani et al. 1992; Allen et al. 2006), consistent with evidence that retail traders often trade in the direction of perceived sentiment (Barber, Odean, and Zhu 2009). Alternatively, investors may lean against others' beliefs when they read them as evidence of a sentiment- or noise-driven component in prices (Park and Sabourian 2011; Eyster and Rabin 2014; Bastianello and Fontanier 2025; Gorodnichenko and Yin 2026). Our model in Section II delivers a prediction as a combination of the two: Proposition 2 implies retail order flow loads negatively on HOB, because retail's noisier signal leaves their posterior valuation below the equilibrium price. That is, even if anticipating speculative opportunities, higher-order uncertainty makes retail less assured on realizing such opportunities, but instead believing the price has been too high. By separately extracting investors' first-order sentiment, higher-order sentiment, and the fraction of HOB posts, our measures allow a direct test of retail trading activities on higher-order sentiment.

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 *First-*

order Sentiment: a one-standard-deviation rise in investors' *First-order Sentiment* is associated with roughly a 0.09-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' *First-order Sentiment*, *Relative Sentiment* enters modestly negatively, and the effect is economically small but systematic: a one-standard-deviation increase in *Relative Sentiment* is accompanied with 0.008 standard deviations (0.026 of its IQR) lower retail buying. This indicates that retail traders buy slightly more when they perceive others as more pessimistic, consistent with the contrarian response predicted by Proposition 1.

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 0.011-standard-deviation decline in *Total Order Flow*, indicating a sizable increase in retail participation when investors perceive others as more pessimistic. Columns (3)-(6) show that this decline reflects symmetric adjustments on both sides of the market. Higher *Relative Sentiment* is associated with a 0.011-standard-deviation reduction in *Retail Buy Order* and a 0.011-standard-deviation reduction in *Retail Sell Order*, suggesting that investors scale back both buying and selling rather than shifting positions across sides. By contrast, first-order sentiment moves strongly positively with retail trading activity across all specifications, indicating that investors' own outlook remains a primary driver of retail participation. In the end, Columns (7) and (8) of Table 5 show that, to the opposite of retail trading, *Non-Retail Order Imbalance* increases with *Relative Sentiment*.

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 Sentiment* 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 uncertainty (*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 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.

The heterogeneity by HOB uncertainty in column (1) is consistent with Proposition 4, which predicts that the magnitude of retail contrarian trading is increasing in retail's HOB uncertainty: when investors are less confident about their inferences regarding others' beliefs, the wedge between the equilibrium price loading and retail's posterior valuation widens, amplifying the contrarian response. The remaining interactions, return volatility and idiosyncratic volatility (columns 2–3), are also broadly consistent with this mechanism.[7]

In addition, retail investors are more contrarian when retail trading activity itself is high. This is consistent with Proposition 5. Column (4) shows that the interaction between *Relative Sentiment* and the high-retail indicator is strongly negative, with a magnitude comparable to the volatility-based interactions: a one-standard-deviation increase in relative sentiment is associated with a 0.10-standard-deviation (0.28 of its IQR) decline in retail order imbalance in high-retail-activity periods.

In the end, retail trading is more contrarian when stocks are 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 0.04 or 0.10 standard deviations for stocks with smaller size or larger bid-ask spreads.

Taken together, retail trading reflects both investors' *First-order Sentiment* and their perceptions of others' sentiment, but the strength of these responses varies sharply across environments. On average, retail traders buy more when they are optimistic themselves but become net sellers when the sentiment they attribute to others is more positive, the opposite of the response we observe for non-retail traders. The net-selling

[7] We caution that HOB uncertainty is an imperfect proxy for the HOB signal precision in the model, since it may also reflect other firm characteristics including message ambiguity or stock-specific attention. The mapping to Proposition 4 is therefore more suggestive.

association of retail to higher-order sentiment becomes much stronger when uncertainty is high, retail participation is intense, or liquidity is depressed, environments in which retail's signal about others' beliefs is plausibly noisiest.

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 these sentiment measure predict 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. Returns are annualized for easier interpretability. First, 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 first-order sentiment negatively predict return in the next week. In particular, each standard deviation higher *First-order Sentiment* in the current week predicts a 5.2% lower return in the next week. From Panel B, the predictability is weaker over three weeks, with each standard deviation higher *First-order Sentiment* predicting a slightly significant 6.2% negative return over the next three weeks.

In contrast, the sign is opposite for *Higher-order Sentiment*. In Panel A column (1), each standard deviation higher *Higher-order Sentiment* predicts a 5.6% higher return in the next week. From Panel B, return continues to increase over the following two weeks: each standard deviation higher *Higher-order Sentiment* in the current week predicts a 12.2% 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 activities. 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.

In Figure 7, we plot the coefficients if regressing return on *Higher-order Sentiment* and *First-order Sentiment* at horizons from the two weeks earlier to four weeks ahead. The specification is

$$r_{i,t+h} = \alpha_{t+h} hs_{i,t} + \beta_{t+h} fs_{i,t} + X_{i,t}\Gamma + \epsilon_{i,t+h},$$

where for stock i in week t, $r_{i,t+h}$ is the annualized return in week $t+h$, $hs_{i,t}$ and $fs_{i,t}$ are respective *Higher-order Sentiment* and *First-order Sentiment* in week t, and $X_{i,t}$ contains the controls four weeks ago[8]. α_{t+h} and β_{t+h} therefore measure the relationship between the sentiment measures and return in week $t+h$.

Several patterns emerge. First, both *Higher-order Sentiment* and *First-order Sentiment* are positively associated with contemporaneous returns, and the association between *First-order Sentiment* and contemporaneous returns is much stronger. Specifically, a one-standard-deviation increase in *Higher-order Sentiment* is associated with approximately 10% higher returns in the same week. Meanwhile, a one-standard-deviation increase in *First-order 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 higher-order sentiment, returns continue to be positive for three more weeks, after which return converges back to zero. On the other hand, *First-order Sentiment* predicts negative return in the next week. The reversal pattern is consistent with investors overreacting to *First-order Sentiment*, leading to over-pricing. Meanwhile, beyond week $t+1$, *First-order Sentiment* does not predict returns in further future. This difference between return dynamics around *Higher-order Sentiment* and *First-order 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, *Higher-order Sentiment* is unlikely a mere derivative of *First-order Sentiment*, and the two sentiment measures have different impacts on trading behaviors, which lead to different

[8] Controls include Fraction HOB, Disagreement, MOM-1M, Lag. TURN, E/P, BM, SIZE, PROF, INV, LEV, IVOL.

return dynamics.

C. Discussion

Taken together, Tables 4 to 7 show that higher HOB sentiment is associated with (*i*) positive contemporaneous returns, (*ii*) reduced net retail buying alongside elevated net non-retail buying, and (*iii*) positive short-horizon return predictability, with continuation strongest where retail activity is more intensive and HOB posts are more uncertain. These patterns line up jointly with the model in Section II. When investors attribute more optimistic beliefs to others, the current price rises because all traders price in the expected resale value (Proposition 1). Retail's signal about HOB is noisier than institutions', and the equilibrium price loads on the population-weighted posterior, so the price sits above retail's own posterior. Retail therefore reacts less to the HOB signal than institutions and becomes a net seller (Proposition 2). The price also under-incorporates the higher-order component, and the unincorporated portion is realized as the consensus is revealed in the next period, producing positive return continuation (Proposition 3). The cross-sectional pattern that continuation strengthens with retail intensity and signal uncertainty maps directly to Propositions 4 and 5.

Broadly, there are two possibilities such that contrarian trading can lead to higher future return. First, net selling pressure compresses current price below its fair value, which leads to price reversal in the next period (See He and Wang (1996) and Bacchetta and Van Wincoop (2008) for examples). Second, like in the model in Section II, even though both retail and institutional traders ride on HOB, but given a more inertia expectation formation of the retail traders, price gets pushed higher than retail’s valuation because institutional traders are stronger in executing on the same speculative signals, inducing a net selling behavior of the retail. The former is associated with negative current period return, while the latter is associated with positive current period return. Our results therefore are consistent with the latter.

VII. Robustness of the Results

Online Appendix Section II 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 higher-order sentiment, retail trading, and returns are not driven by particular time periods, modeling assumptions, or empirical design choices.

First, we examine robustness across different subsamples. In Tables A.1 to A.3, we show that the patterns for higher-order posting, higher-order 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 higher-order sentiment and first-order sentiment, one concern is that its association with trading and returns could mechanically reflect the negative loading on first-order sentiment. All our main specifications explicitly control for first-order sentiment, so the estimated coefficient on relative sentiment captures variation orthogonal to investors' own views. Nevertheless, in Table A.4, we further verify that the results are preserved when replacing relative sentiment with higher-order sentiment directly. Across these specifications, the qualitative relationships between beliefs about others, retail trading, and returns remain unchanged.

An additional concern is whether our results depend on the specific LLM used for classification and sentiment extraction. We adopt Gemini 2.0 Flash as our benchmark for tractability, as more advanced reasoning models are roughly twenty times slower and substantially more costly at the scale of 46 million messages. To assess robustness, we replicate the classification and sentiment tasks using GPT-5-mini on a random sample of 10,000 posts (5,000 HOB posts and 5,000 non-HOB posts). As reported in Panel A of Table A.5, the two models produce highly correlated higher-order sentiment measures (correlation = 0.70), and HOB classification agreement exceeds 81%. Some discrepancy is expected given differences in training data and semantic priors, particularly for opinion-

based tasks (Frénay and Verleysen, 2013). In addition, we also randomly select 1,000 posts, and hand code if the posts are HOB posts by three human research assistants. From Panel B of Table A.5, HOB classification agreement between Gemini 2.0 and human also exceeds 80%, indicating the robustness of using Gemini for HOB posts classification.

To further address model-specific variation, we explicitly account for cross-model discrepancies following the computer science literature (Hinton et al. 2015). Using the 10,000-post sample, we train a prediction model to map Gemini-based features into GPT-based classifications and sentiment scores, construct GPT-implied firm-week measures, and re-estimate our main specifications. Table A.6 shows that the coefficients on higher-order and relative sentiment remain virtually unchanged, and the differences between Gemini- and GPT-based measures are generally insignificant. These results suggest that cross-model variation primarily reflects classical measurement noise rather than systematic bias.

In addition, in Table A.7, 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.

In the end, despite starting with over 46 million posts, the median firm-week contains only two HOB posts. This raises concerns that the results may be driven by measurement error arising from the small number of observations. To address this issue, we repeat our main analysis using only firm-weeks with an above-median number of HOB posts (at least three). The results, reported in Table A.8 of the Online Appendix, remain robust after excluding the half of the sample with below-median HOB counts, suggesting that our findings are not driven by the limited number of HOB posts.

VIII. Conclusion

This paper studies how investors perceive the sentiment of others and how these perceptions relate to trading and price dynamics in financial markets. Using more than 46 million StockTwits posts, we apply LLM 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 higher-order sentiment and first-

order sentiment, objects that are central in theories but have been difficult to observe empirically.

We show that references to others are common and systematically differ from investors' own views, and that higher-order sentiment varies with disagreement, valuation, returns, and market uncertainty. Linking these beliefs to market outcomes, we find that retail traders buy more when their first-order 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 first-order sentiment, which predicts reversals. Taken together, these findings provide large-scale evidence that higher-order sentiment are distinct from first-order sentiment and play a systematic, state-dependent role in shaping retail trading behavior and 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 higher-order sentiment is also a macroeconomic state variable that impacts risk premium. 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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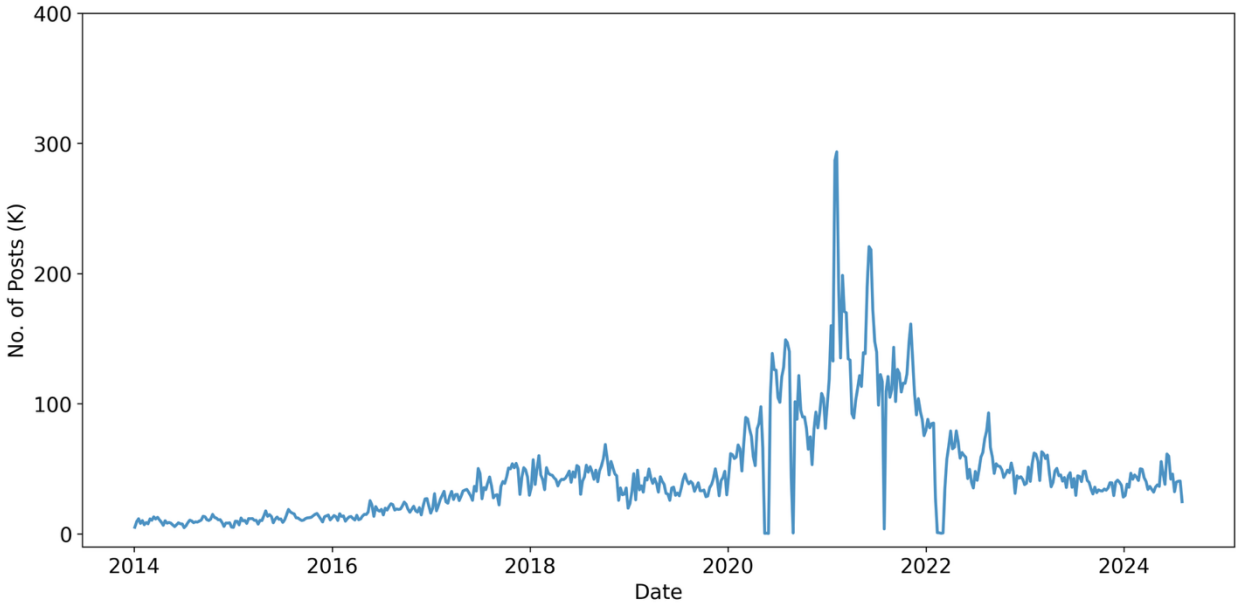
Figure 1: Number of Weekly Posts



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

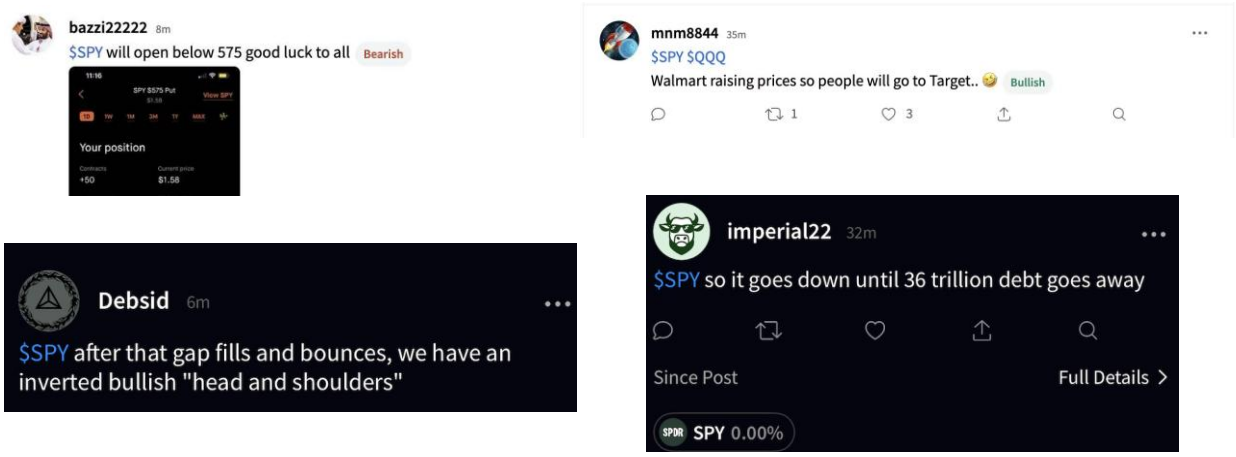
C: HOB - FOB

D: Expectation - Rationalization

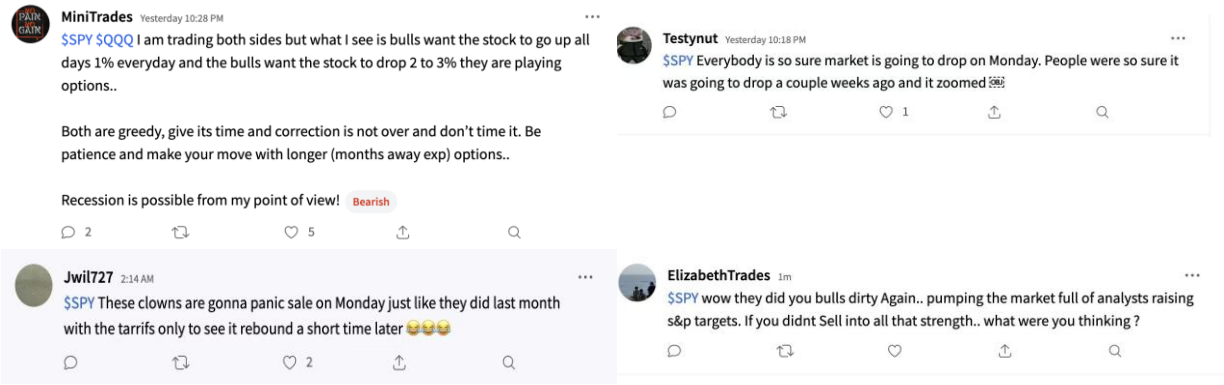
Note: This figure presents word clouds constructed from StockTwits messages. Panel A shows FOB messages, which express investors' own views without mentioning others' beliefs or actions. Panel B displays a word cloud based on HOB messages—posts that explicitly refer to others' beliefs or actions. Panel 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



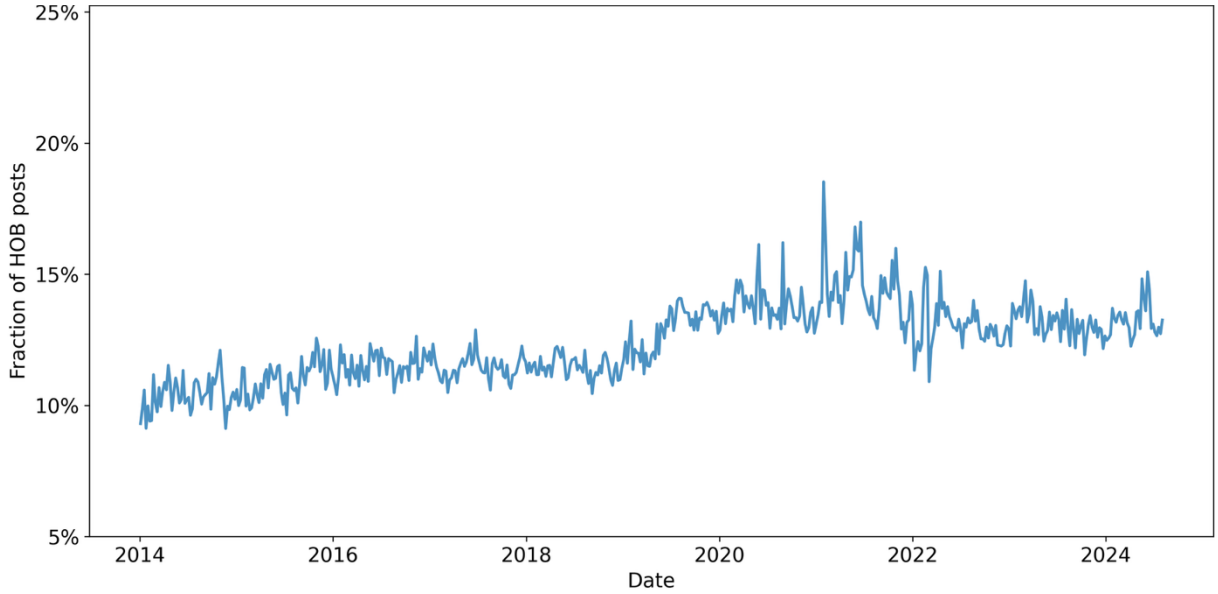
B: HOB



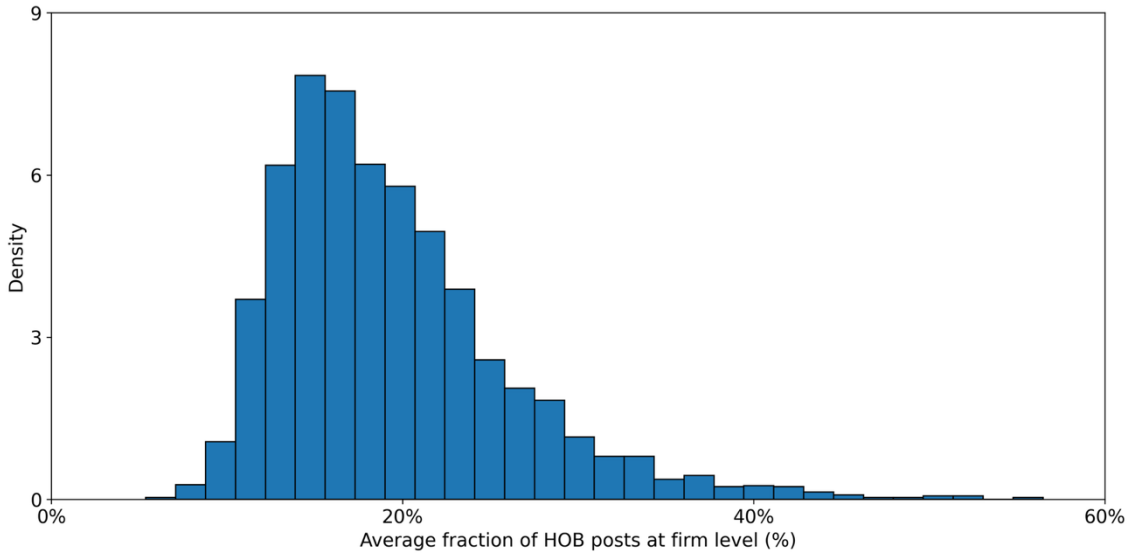
Note: Panel A and Panel B of this figure respectively give examples of the message classified as FOB and HOB.

Figure 4: Fraction of HOB Posts

A: Time-Series Evolution



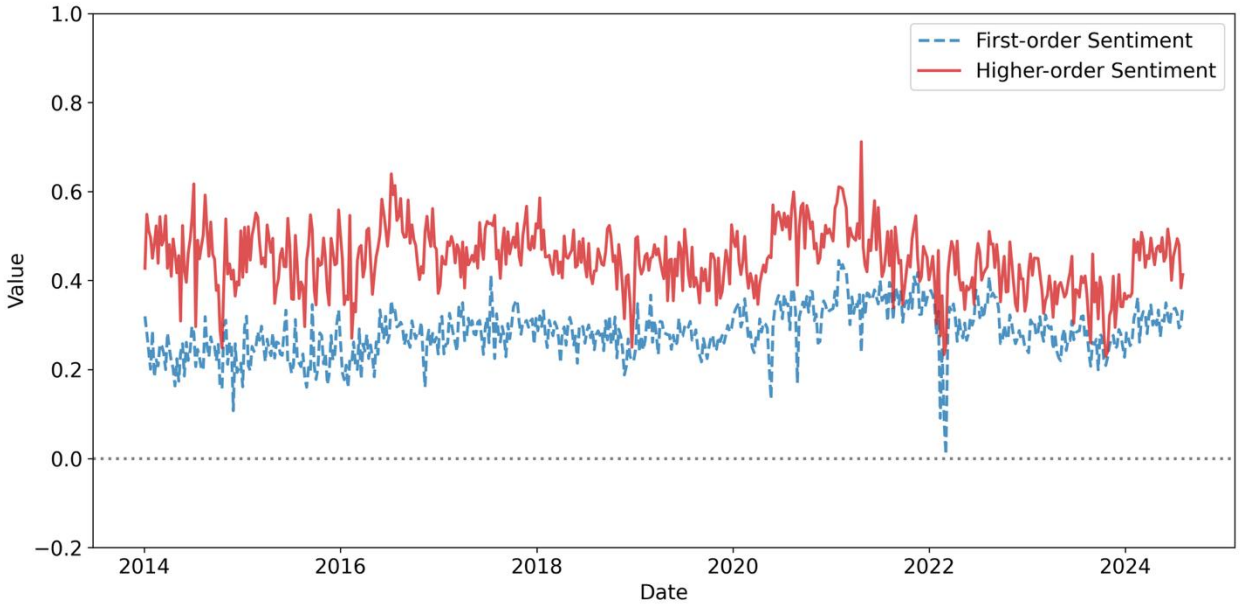
B: Cross-Section of Firm Averages



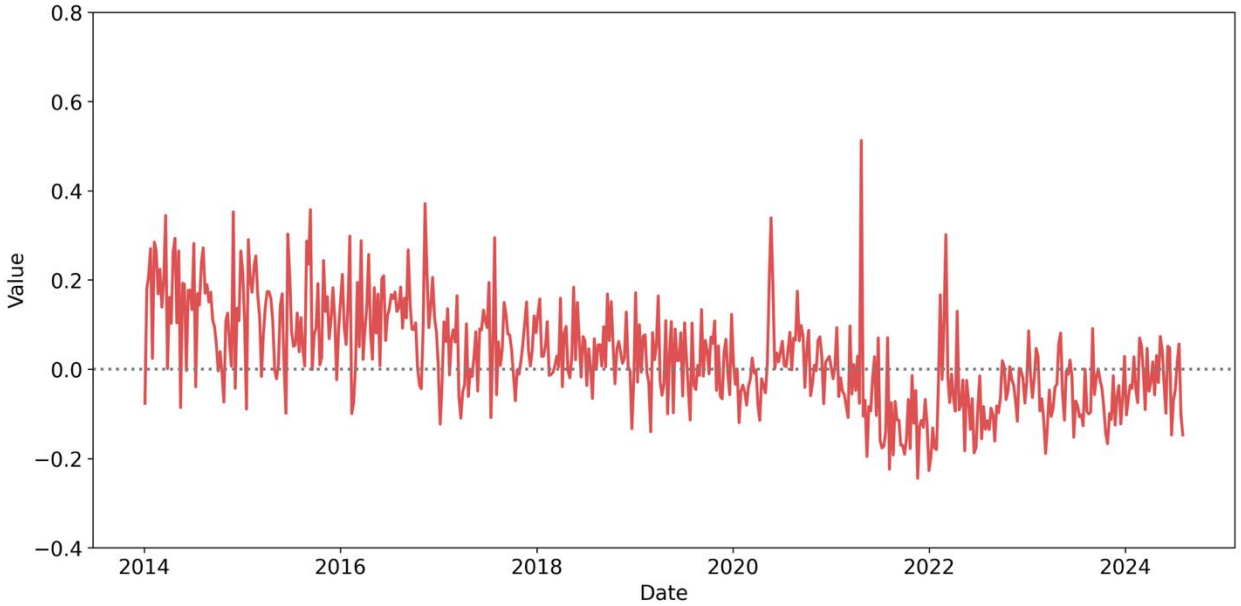
Note: Panel A shows the weekly fraction of posts that references to others' belief or actions (Fraction HOB) in our sample from January 2014 to July 2024. Panel B plots the distribution of the firm-level average fraction of higher-order-belief (HOB) messages. For each firm, we compute the mean share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

Figure 5: Time Series of Higher-order, First-order and Relative Sentiment

Panel A: Higher-order and First-order Sentiment

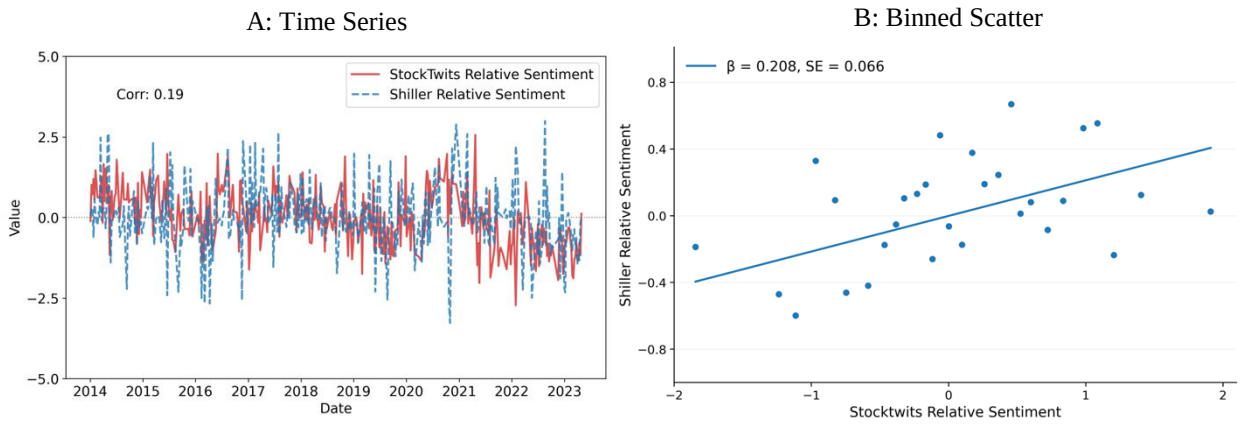


Panel B: Relative Sentiment



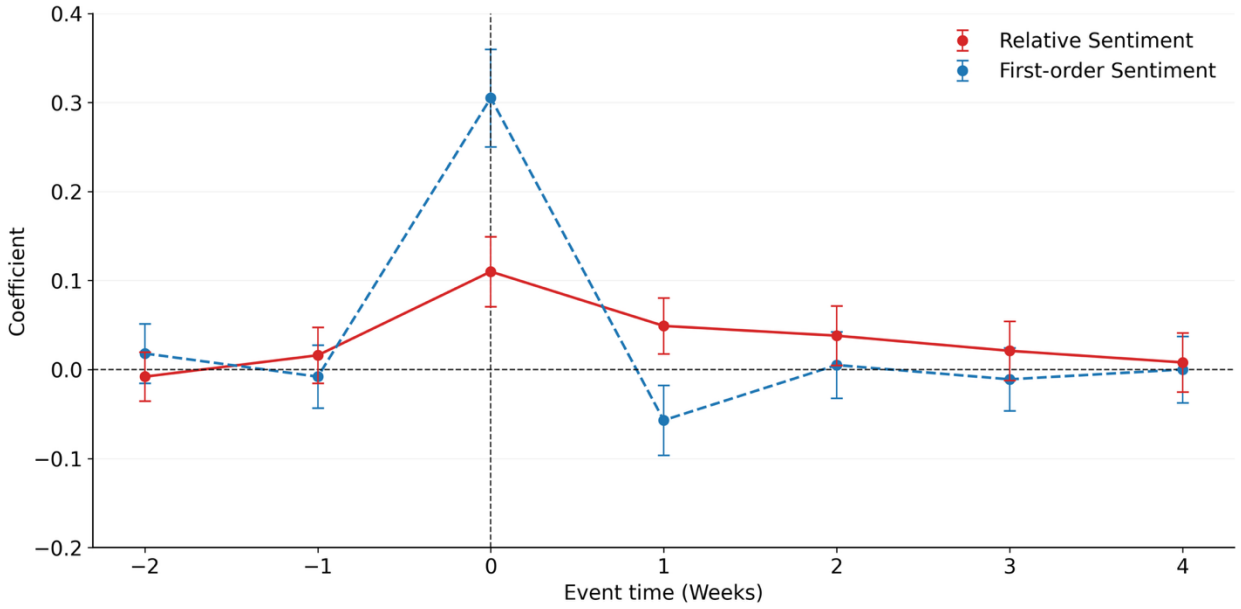
Note: This figure plots the weekly time series of first-order sentiment (*First-order Sentiment*), higher-order sentiment (*Higher-order sentiment*) and relative sentiment (*Relative sentiment*) from January 2014 to July 2024. Panel A shows the objective and higher-order sentiment, where the blue dashed line represents first-order sentiment and the green dotted line represents higher-order sentiment. Panel B displays the weekly time series of Relative Sentiment, constructed as the difference between standardized higher-order sentiment (*Higher-order sentiment*) and standardized first-order sentiment (*First-order 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 residualized values from regressing top 100 largest companies' average *Relative Sentiment* on top 100 largest companies' average *First-order 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 0.19. Panel B shows a binscatter plot of Shiller Relative Sentiment on Stocktwits Sentiment. Standard errors are adjusted Newey-West with three lags.

Figure 7: Return Dynamics Relative Sentiment and First-order 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 First-order 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	120.998	889.280	10.000	24.000	68.000	210561
N HOB Posts	15.980	152.053	1.000	2.000	7.000	210561
Fraction HOB	0.150	0.100	0.086	0.125	0.182	210561
Higher-order Sentiment	0.450	0.672	0.000	0.667	1.000	210561
First-order Sentiment	0.299	0.488	0.000	0.000	0.859	210561
Relative Sentiment	0.000	1.231	-0.962	-0.169	1.430	210561
HOB Uncertainty	0.128	0.056	0.100	0.100	0.137	210561
Disagreement	0.538	0.382	0.000	0.603	0.882	210561
Market Cap	30.818	14.666	0.066	0.466	5.401	210561
BM	0.617	0.807	0.159	0.344	0.756	210561
INV	0.421	1.247	-0.088	0.065	0.398	210561
PROF	-0.302	0.496	-0.489	-0.132	0.026	210561
LEV	0.481	0.261	0.256	0.485	0.690	210561
E/P	-0.452	1.189	-0.370	-0.067	0.021	210561
RET	-0.001	0.155	-0.059	-0.001	0.053	210561
Ret Volatility	0.050	0.082	0.021	0.035	0.057	210561
MOM-1M	-0.021	0.279	-0.132	-0.011	0.095	210561
TURN	0.196	0.449	0.038	0.077	0.160	210561
IVOL	0.040	0.035	0.019	0.030	0.048	210561
Retail Order Imbalance	0.288	1.409	-0.108	0.028	0.291	181501
Total Retail Order	11.972	36.348	0.941	2.418	6.752	181501
Retail Buy Order	6.146	18.700	0.468	1.223	3.462	181501
Retail Sell Order	5.814	17.595	0.456	1.177	3.297	181501
Non-Retail Order Imbalance	-0.629	2.279	-0.641	-0.133	0.107	177421

Note: N Posts, N HOB Posts and Fraction HOB denote 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. Higher-order Sentiment and First-order Sentiment measures the average of higher-order sentiment (HOB sentiment) and first-order sentiment (FOB sentiment) at firm week level, respectively. The Relative Sentiment measures the difference between standardized Higher-order Sentiment and First-order Sentiment. The Disagreement shows the standard deviation of investors' First-order 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, Retail Sell Order and Non-Retail Order Imbalance represent the total retail order flow, retail buying order flow, retail selling order flow and non-retail order imbalance, 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 (TURN), 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). All variables are winsorized at the 1%-99% level.

Table 2: Fraction of HOB

	(1)	(2)	(3)	(4)	(5)
Dep Var:			Fraction HOB		
Higher-order Sentiment	0.002	-0.195***	-0.193***	-0.197***	-0.200***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)
First-order Sentiment	0.207***	0.129***	0.132***	0.134***	0.179***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Disagreement		-0.866***	-0.878***	-0.872***	-0.851***
		(0.039)	(0.039)	(0.039)	(0.039)
RET			-0.895***	-0.945***	-0.865***
			(0.139)	(0.143)	(0.145)
E/P				0.358***	0.257***
				(0.052)	(0.055)
BM				0.081	0.048
				(0.061)	(0.061)
SIZE				-0.653***	-0.843***
				(0.207)	(0.212)
PROF					0.214***
					(0.064)
INV					-0.117***
					(0.042)
LEV					-0.103
					(0.083)
MOM-1M					0.326***
					(0.092)
IVOL					-0.573***
					(0.034)
Firm FE	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes
N	210053	210053	210053	210053	210053
R-sq	0.183	0.188	0.189	0.189	0.191

Note: This table examines the fraction of HOB posts (Fraction HOB) relates to higher order sentiment, first order sentiment, disagreement measures, and valuation metrics. In column (1), we regress Fraction HOB on Higher-order Sentiment and First-order Sentiment. Columns (2) and (3) further include the disagreement in first-order 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). All variables are winsorized at 1% - 99% level and standardized except RET, MOM-1M and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 3: Higher-order Sentiment

	(1)	(2)	(3)	(4)
Dep Var:		Higher-order Sentiment		
First-order Sentiment	0.194***	0.194***	0.194***	0.195***
	(0.005)	(0.005)	(0.005)	(0.005)
Fraction HOB	-0.195***	-0.193***	-0.197***	-0.201***
	(0.028)	(0.028)	(0.028)	(0.028)
Disagreement	-0.684***	-0.681***	-0.682***	-0.682***
	(0.009)	(0.009)	(0.009)	(0.009)
RET		0.082***	0.094***	0.088***
		(0.012)	(0.012)	(0.012)
E/P			0.020***	0.021***
			(0.004)	(0.004)
BM			-0.001	0.001
			(0.004)	(0.005)
SIZE			-0.126***	-0.118***
			(0.014)	(0.015)
PROF				0.001
				(0.005)
INV				-0.004
				(0.003)
LEV				-0.001
				(0.005)
MOM-1M				-0.045***
				(0.008)
IVOL				-0.009***
				(0.003)
Firm FE	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes
N	210053	210053	210053	210053
R-sq	0.185	0.185	0.185	0.185

Note: This table examines the higher-order sentiment (Higher-order Sentiment) relates to first order belief, disagreement measures, and valuation metrics. In column (1), we regress higher-order sentiment on first-order sentiment (First-order Sentiment), fraction of HOB posts (Fraction HOB), the disagreement in first-order sentiment (Disagreement). Columns (2) 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). All variables are winsorized at 1% - 99% level and standardized except RET, MOM-1M and Fraction HOB. 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	-0.076***	-0.018***	-0.023***	-0.007***	-0.007***	-0.008***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
First-order Sentiment		0.093***	0.079***	0.099***	0.087***	0.093***
		(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
Fraction HOB				-0.518***	-0.450***	-0.454***
				(0.028)	(0.028)	(0.028)
Disagreement				0.159***	0.135***	0.124***
				(0.009)	(0.008)	(0.008)
MOM-1M					-0.340***	-0.243***
					(0.028)	(0.026)
TURN					0.254***	0.229***
					(0.030)	(0.029)
IVOL					0.024***	0.012*
					(0.006)	(0.006)
E/P						-0.114***
						(0.014)
BM						-0.035***
						(0.009)
SIZE						-0.196***
						(0.025)
PROF						0.044***
						(0.011)
INV						-0.003
						(0.006)
LEV						-0.008
						(0.009)
Firm FE	No	No	Yes	Yes	Yes	Yes
Yearwk FE	No	No	Yes	Yes	Yes	Yes
N	181501	181501	181055	181055	181055	181055
R-sq	0.006	0.011	0.094	0.099	0.114	0.124

Note: This table examine how higher-order 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 First-order 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 first-order 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, Lag. TURN and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 5: Trading Activities

Dep Var:	(1) Total Retail Volume	(2) Total Retail Volume	(3) Retail Buy	(4) Retail Buy	(5) Retail Sell	(6) Retail Sell	(5) Non-Retail Imbalance	(6) Non-Retail Imbalance
Relative Sentiment	-0.036***	-0.011***	-0.036***	-0.011***	-0.036***	-0.011***	0.028***	0.008***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
First-order Sentiment	0.119***	0.108***	0.119***	0.109***	0.119***	0.107***	-0.078***	-0.084***
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)
Fraction HOB		-0.478***		-0.483***		-0.472***		0.378***
		(0.033)		(0.033)		(0.033)		(0.029)
Disagreement		0.157***		0.159***		0.156***		-0.146***
		(0.010)		(0.010)		(0.010)		(0.009)
MOM-1M		-0.020		-0.030		-0.010		0.213***
		(0.019)		(0.019)		(0.019)		(0.021)
TURN		0.836***		0.820***		0.851***		-0.483***
		(0.027)		(0.027)		(0.026)		(0.028)
IVOL		0.060***		0.058***		0.061***		-0.044***
		(0.006)		(0.006)		(0.006)		(0.005)
E/P		-0.088***		-0.091***		-0.084***		0.138***
		(0.010)		(0.010)		(0.010)		(0.014)
BM		0.027***		0.025***		0.030***		0.029***
		(0.008)		(0.008)		(0.008)		(0.009)
SIZE		-0.060***		-0.067***		-0.054**		0.224***
		(0.022)		(0.022)		(0.023)		(0.024)
PROF		0.024***		0.025***		0.021**		-0.035***
		(0.009)		(0.009)		(0.009)		(0.010)
INV		-0.018***		-0.017***		-0.018***		0.012*
		(0.006)		(0.006)		(0.006)		(0.006)
LEV		0.026***		0.025***		0.027***		-0.009
		(0.008)		(0.008)		(0.008)		(0.009)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	181055	181055	181055	181055	181055	181055	176991	176991
R-sq	0.228	0.352	0.226	0.346	0.230	0.358	0.174	0.240

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 First-order 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. Column (7) and (8) examine the relative sentiment (Relative Sentiment) affects non-retail order imbalance (Non-Retail Imbalance), where the Non-Retail Imbalance is defined as difference between total order imbalance (Total Order Imbalance) and retail order imbalance (Retail Order Imbalance). All variables are winsorized at 1% - 99% level and standardized except MOM-1M, Lag. TURN and Fraction HOB. 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

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:			Retail Order Imbalance			
Relative Sentiment	0.016***	0.038***	0.025***	0.040***	0.037***	0.040***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Relative Sentiment x Uncertainty H	-0.104***					
	(0.006)					
Relative Sentiment x RET Volatility H		-0.102***				
		(0.005)				
Relative Sentiment x IVOL H			-0.073***			
			(0.005)			
Relative Sentiment x Retail Trades H				-0.114***		
				(0.006)		
Relative Sentiment x SIZE L					-0.041**	
					(0.016)	
Relative Sentiment x Bid-Ask Spread H						-0.104***
						(0.005)
Uncertainty H	0.175***					
	(0.008)					
RET Volatility H		0.215***				
		(0.008)				
IVOL H			0.013*			
			(0.007)			
Retail Trades H				0.147***		
				(0.011)		
SIZE L					-0.093***	
					(0.006)	
Bid-Ask Spread H						0.200***
						(0.008)
Firm Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	181055	181055	181055	181055	181055	181049
R-sq	0.132	0.135	0.125	0.128	0.126	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 First-order Sentiment, Fraction HOB, Disagreement, MOM-1M, Lag. TURN, IVOL, E/P, BM, SIZE, PROF, INV, LEV. All variables are winsorized at 1% - 99% level and standardized except RET, MOM-1M, Lag. TURN and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 7: Return Predictability

	(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	0.056***	0.003	0.128***	-0.020	0.151***	0.053***	0.088**	0.078***	0.035**	0.012	0.106***
	(0.016)	(0.018)	(0.035)	(0.016)	(0.031)	(0.018)	(0.036)	(0.030)	(0.016)	(0.016)	(0.031)
First-order Sentiment	-0.052***	-0.017	-0.088**	-0.024	-0.048	-0.006	-0.086**	-0.094***	-0.009	0.010	-0.104***
	(0.019)	(0.021)	(0.040)	(0.019)	(0.033)	(0.022)	(0.040)	(0.034)	(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	208089	89679	89306	104026	103309	117724	89702	103774	104040	104067	103319
R-sq	0.141	0.211	0.148	0.190	0.146	0.160	0.154	0.139	0.215	0.200	0.144
	Panel B: Return in 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	0.122***	0.030	0.224***	0.009	0.249***	0.068**	0.302***	0.160***	0.073***	0.036	0.204***
	(0.029)	(0.031)	(0.064)	(0.029)	(0.056)	(0.032)	(0.067)	(0.053)	(0.028)	(0.028)	(0.056)
First-order Sentiment	-0.062*	0.002	-0.141**	0.010	-0.089	0.011	-0.052	-0.121*	-0.013	0.047	-0.155**
	(0.035)	(0.034)	(0.072)	(0.033)	(0.060)	(0.038)	(0.069)	(0.063)	(0.032)	(0.032)	(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	208089	89679	89306	104026	103309	117724	89702	103774	104040	104067	103319
R-sq	0.186	0.250	0.201	0.220	0.195	0.194	0.212	0.187	0.249	0.229	0.194

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, First-order Sentiment, controlling Fraction HOB, disagreement in first-order sentiment (Disagreement), contemporaneous returns (RET), Lagged turnover (Lag. TURN), 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, which is defined as the total retail order flow (Total Retail Order) over the turnover (TURN). 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, MOM-1M, Lag. TURN and Fraction HOB. 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

I. Proof

Proof of Lemma 1. Market clearing $X^H + X^L = Q_0$ equates the aggregate demand in (7) to supply. This gives

$$\nu_0 + [\phi A_H + (1-\phi)A_L]B_0 - [\phi\psi_H + (1-\phi)\psi_L]\rho Q_0/l = Q_0/\chi + p_0.$$

Matching coefficients on B_0 gives

$$l = \phi A_H + (1-\phi)A_L.$$

Matching coefficients on Q_0 gives

$$\rho = \frac{l}{\chi\bar{\alpha}}, \qquad \bar{\alpha} \equiv \phi\alpha_H + (1-\phi)\alpha_L.$$

Substituting this expression for ρ into the definition of γ gives

$$\frac{\gamma}{1-\gamma} = \frac{\chi^2\bar{\alpha}^2\sigma_B^2}{\sigma_Q^2}, \tag{A.1}$$

where l cancels. Substituting

$$\alpha_k(\gamma) = \frac{\omega_k(1-\gamma)}{1-\omega_k\gamma}$$

into $\bar{\alpha}$ makes the right-hand side of (A.1) a function of γ alone. For each k,

$$\frac{\partial\alpha_k}{\partial\gamma} = -\frac{\omega_k(1-\omega_k)}{(1-\omega_k\gamma)^2} < 0,$$

so the right-hand side of (9) is strictly decreasing in γ. The left-hand side, $\gamma/(1-\gamma)$, is strictly increasing from 0 to ∞ on (0,1). At $\gamma = 0$, the left-hand side is zero and the right-hand side is positive; as $\gamma \to 1$, the left-hand side diverges and the right-hand side converges to zero. Therefore there exists a unique solution $\gamma \in (0,1)$.

For the ordering, since $\omega_k, \gamma \in (0,1)$,

$$\alpha_k = \frac{\omega_k(1-\gamma)}{1-\omega_k\gamma} > 0, \qquad \psi_k = \frac{\gamma(1-\omega_k)}{1-\omega_k\gamma} > 0,$$

so $A_k = \alpha_k + \psi_k > 0$. Since

$$\frac{\partial A_k}{\partial \omega_k} = \frac{(1-\gamma)^2}{(1-\omega_k\gamma)^2} > 0,$$

we have $A_H > A_L > 0$. The price loading $l = \phi A_H + (1-\phi)A_L$ is a strict convex combination, so $0 < A_L < l < A_H$. Finally,

$$A_k - 1 = -\frac{(1-\omega_k)(1-\gamma)}{1-\omega_k\gamma} < 0,$$

so $A_H < 1$ and therefore $l < 1$. This establishes $0 < A_L < l < A_H < 1$. □

Proof of Propositions 1-3. Proposition 1 reads off the coefficient on B_0 in (5), after taking expectations over Q_0. For Proposition 2, the B_0 coefficients in (8) are $(1-\phi)\chi(A_L - l)$ and $\phi\chi(A_H - l)$. Since $A_L < l < A_H$ by Lemma 1, the first coefficient is negative and the second is positive. For Proposition 3,

$$\hat{E}[r_1 \mid B_0, \mu_0] = \hat{E}[p_1 \mid B_0, \mu_0] - \hat{E}[p_0 \mid B_0, \mu_0].$$

Using (3), (4), and (5), this becomes

$$\hat{E}[r_1 \mid B_0, \mu_0] = \left(\beta_\mu\mu_0 + B_0\right) - \left(\beta_\mu\mu_0 + lB_0\right) = (1-l)B_0.$$

Thus $\partial\hat{E}[r_1 \mid B_0, \mu_0]/\,\partial B_0 = 1 - l > 0$ by Lemma 1. □

Proof of Proposition 4. Since $l = \phi A_H + (1-\phi)A_L$,

$$l - A_L = \phi(A_H - A_L).$$

Using the expression for A_k,

$$A_H - A_L = \frac{(1-\gamma)^2(\omega_H - \omega_L)}{(1-\omega_H\gamma)(1-\omega_L\gamma)}. \tag{A. 2}$$

At a fixed γ, increasing ω_L lowers $A_H - A_L$ because A_L is strictly increasing in ω_L. In equilibrium, increasing ω_L also increases γ. To see this, define

$$F(\gamma, \omega_L) \equiv \frac{\gamma}{1-\gamma} - \frac{\chi^2\sigma_B^2}{\sigma_Q^2}\bar{\alpha}(\gamma, \omega_L)^2.$$

The equilibrium value of γ solves $F(\gamma, \omega_L) = 0$. Since $\partial F/\,\partial\gamma > 0$ and $\partial F/\,\partial\omega_L < 0$, the implicit-function theorem gives $d\gamma/d\omega_L > 0$.

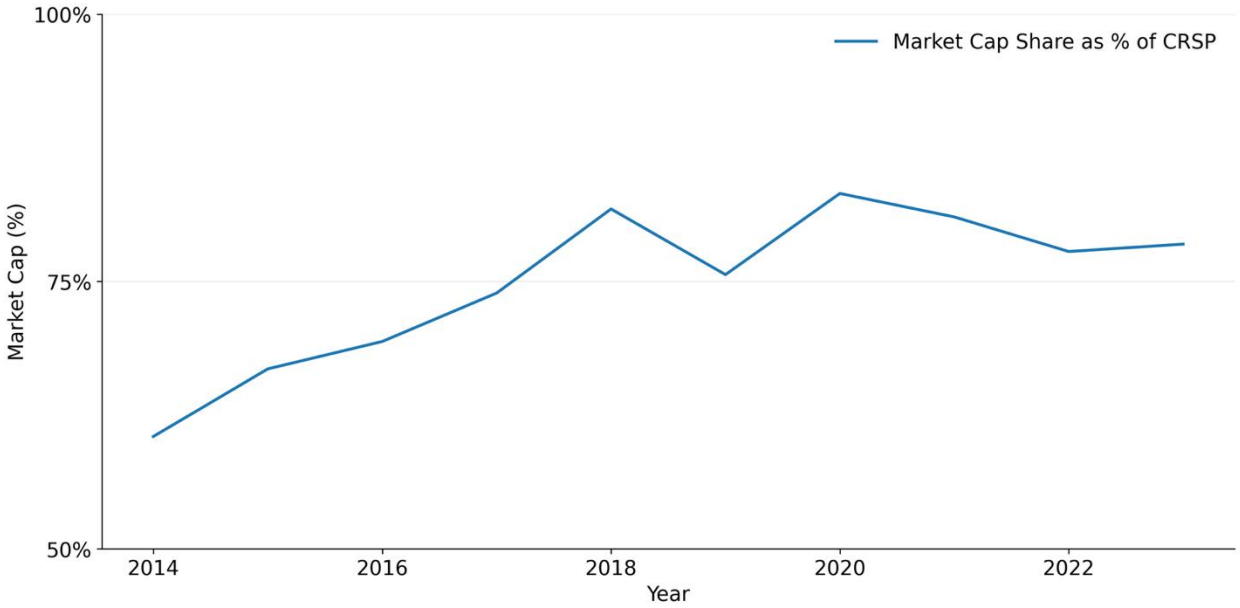
It remains to note that $A_H - A_L$ is strictly decreasing in γ. From (A.2),

$$\frac{\partial \log(A_H - A_L)}{\partial \gamma} = -\frac{2}{1-\gamma} + \frac{\omega_H}{1-\omega_H\gamma} + \frac{\omega_L}{1-\omega_L\gamma} < 0,$$

because $\omega_k/(1-\omega_k\gamma) < 1/(1-\gamma)$ for each $k \in \{H, L\}$. Therefore both channels generated by an increase in ω_L lower $A_H - A_L$. Since $l - A_L = \phi(A_H - A_L)$ and $\phi > 0$, $d(l - A_L)/d\omega_L < 0$. □

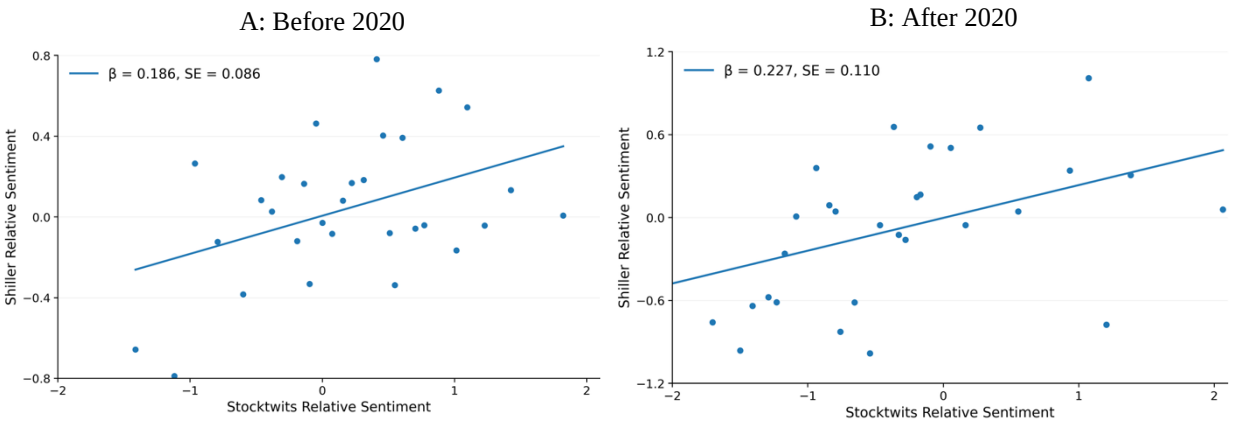
II. Additional Results

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.

Figure A2: Stocktwits Relative Sentiment and Shiller Relative Sentiment (Subsample)



Note: This figure illustrates the relationship between Stocktwits Relative Sentiment and Shiller Relative Sentiment measure. Stocktwits Relative Sentiment is constructed using the residualized values from regressing top 100 largest companies' average *Relative Sentiment* on op 100 largest companies' average *First-order 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 and Panel B shows the binscatter plots before and after 2020, respectively. Standard errors are adjusted Newey-West with three lags.

Table A.1: Fraction of HOB

Dep Var: Fraction HOB	(1) <2018	(2) >=2018	(3) <2020	(4) >=2020	(5) <2022	(6) >=2022
Relative Sentiment	0.089	-0.369***	-0.056	-0.394***	-0.215***	-0.273***
	(0.065)	(0.038)	(0.049)	(0.047)	(0.043)	(0.056)
First-order Sentiment	0.321***	-0.064	0.239***	-0.044	0.057	0.073
	(0.071)	(0.047)	(0.053)	(0.055)	(0.048)	(0.065)
Disagreement	-0.982***	-0.787***	-1.005***	-0.715***	-0.836***	-0.917***
	(0.062)	(0.045)	(0.052)	(0.053)	(0.044)	(0.067)
RET	-1.575***	-0.682***	-1.197***	-0.815***	-1.029***	-0.941***
	(0.280)	(0.167)	(0.211)	(0.192)	(0.183)	(0.236)
E/P	0.306**	0.276***	0.240***	0.282***	0.267***	0.184**
	(0.120)	(0.060)	(0.088)	(0.066)	(0.075)	(0.080)
BM	-0.170	0.031	-0.096	0.113	-0.020	0.127
	(0.153)	(0.070)	(0.112)	(0.080)	(0.077)	(0.106)
SIZE	-0.962*	-1.088***	-0.922***	-0.882***	-0.624**	-0.811*
	(0.526)	(0.248)	(0.331)	(0.282)	(0.257)	(0.449)
PROF	0.150	0.204***	0.239**	0.152*	0.188**	0.154
	(0.176)	(0.072)	(0.101)	(0.088)	(0.079)	(0.158)
INV	-0.131	-0.072	-0.076	-0.069	-0.136**	-0.058
	(0.108)	(0.046)	(0.090)	(0.048)	(0.059)	(0.063)
LEV	-0.279	-0.078	-0.330***	-0.092	-0.191**	-0.196
	(0.176)	(0.099)	(0.121)	(0.114)	(0.095)	(0.185)
MOM-1M	-0.196	0.443***	0.181	0.334***	0.336***	0.008
	(0.189)	(0.103)	(0.139)	(0.119)	(0.109)	(0.150)
IVOL	-0.656***	-0.506***	-0.656***	-0.467***	-0.622***	-0.379***
	(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	47400	162260	87089	122557	146327	63319
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, First-order Sentiment, disagreement in first-order 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 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 A.2: Higher-order Sentiment

Dep Var: Higher-order Sentiment	(1) <2018	(2) >=2018	(3) <2020	(4) >=2020	(5) <2022	(6) >=2022
First-order Sentiment	0.171***	0.200***	0.179***	0.203***	0.179***	0.221***
	(0.008)	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)
Fraction HOB	0.090	-0.289***	-0.052	-0.302***	-0.172***	-0.243***
	(0.064)	(0.029)	(0.045)	(0.035)	(0.034)	(0.049)
Disagreement	-0.648***	-0.679***	-0.672***	-0.666***	-0.710***	-0.579***
	(0.017)	(0.010)	(0.012)	(0.012)	(0.010)	(0.015)
RET	0.078***	0.093***	0.073***	0.105***	0.053***	0.154***
	(0.026)	(0.014)	(0.019)	(0.017)	(0.015)	(0.022)
E/P	-0.003	0.023***	0.016**	0.021***	0.015***	0.020***
	(0.010)	(0.005)	(0.007)	(0.006)	(0.006)	(0.008)
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	-0.006	-0.131***	-0.088***	-0.132***	-0.103***	-0.107***
	(0.041)	(0.017)	(0.028)	(0.022)	(0.018)	(0.036)
PROF	0.016	-0.003	0.006	-0.004	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	-0.008	0.002	-0.009	-0.004	-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*	-0.071***	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	47400	162260	87089	122557	146327	63319
R-sq	0.203	0.195	0.189	0.205	0.188	0.218

Note: This table examines the higher-order sentiment (Higher-order Sentiment) relates to first order sentiment, disagreement measures, and valuation metrics in different sample periods. All regressions show the same specification by regress the Higher-order Sentiment on First-order Sentiment, Fraction HOB, disagreement in first-order 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 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, MOM-1M and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A.3: Retail Order Imbalance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var: Retail Order Imbalance	<2018	>=2018	<2020	>=2020	<2022	>=2022
Relative Sentiment	-0.016**	-0.008***	-0.007**	-0.008***	-0.008***	-0.010**
	(0.007)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
First-order Sentiment	0.056***	0.097***	0.073***	0.106***	0.085***	0.112***
	(0.008)	(0.005)	(0.006)	(0.005)	(0.005)	(0.007)
Fraction HOB	-0.225***	-0.484***	-0.319***	-0.545***	-0.321***	-0.843***
	(0.054)	(0.030)	(0.036)	(0.038)	(0.025)	(0.057)
Disagreement	0.126***	0.127***	0.122***	0.129***	0.138***	0.096***
	(0.018)	(0.009)	(0.012)	(0.011)	(0.010)	(0.014)
MOM-1M	-0.269***	-0.237***	-0.186***	-0.248***	-0.173***	-0.336***
	(0.069)	(0.028)	(0.037)	(0.031)	(0.031)	(0.038)
Lag. TURN	0.187**	0.219***	0.307***	0.183***	0.265***	0.082
	(0.086)	(0.030)	(0.048)	(0.033)	(0.030)	(0.052)
IVOL	-0.003	0.011	-0.004	0.014*	0.013	-0.003
	(0.015)	(0.007)	(0.010)	(0.008)	(0.008)	(0.010)
E/P	-0.369***	-0.108***	-0.193***	-0.095***	-0.133***	-0.105***
	(0.085)	(0.014)	(0.032)	(0.015)	(0.022)	(0.021)
BM	-0.016	-0.037***	-0.018	-0.037***	-0.038***	-0.031**
	(0.031)	(0.009)	(0.020)	(0.011)	(0.011)	(0.015)
SIZE	0.525**	-0.225***	-0.075	-0.254***	-0.172***	-0.221***
	(0.220)	(0.027)	(0.059)	(0.033)	(0.031)	(0.060)
PROF	0.066*	0.041***	0.052***	0.044***	0.042***	0.053*
	(0.036)	(0.011)	(0.017)	(0.015)	(0.012)	(0.029)
INV	0.013	-0.003	-0.003	-0.007	-0.012*	-0.007
	(0.024)	(0.007)	(0.015)	(0.007)	(0.007)	(0.011)
LEV	-0.062	-0.011	-0.003	-0.012	-0.002	-0.039
	(0.046)	(0.009)	(0.014)	(0.013)	(0.010)	(0.024)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18447	162260	58090	122557	117323	63319
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, First-order Sentiment, Fraction HOB, disagreement in first-order sentiment (Disagreement), past 4 weeks excess returns exclude the recent 1 week (MOM-1M), last week turnover (Lag. 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, MOM-1M, Lag. TURN and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table A.4: Retail Order and Higher-order Sentiment

Dep Var:	(1) Retail Order Imbalance	(2) Total Retail Order	(3) Retail Buy Order	(4) Retail Sell Order
Higher-order Sentiment	-0.007***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.001)
First-order Sentiment	0.100***	0.117***	0.118***	0.116***
	(0.004)	(0.006)	(0.006)	(0.006)
Fraction HOB	-0.454***	-0.478***	-0.483***	-0.472***
	(0.028)	(0.033)	(0.033)	(0.033)
Disagreement	0.124***	0.157***	0.159***	0.156***
	(0.008)	(0.010)	(0.010)	(0.010)
MOM-1M	-0.243***	-0.020	-0.030	-0.010
	(0.026)	(0.019)	(0.019)	(0.019)
Lag. TURN	0.229***	0.836***	0.820***	0.851***
	(0.029)	(0.027)	(0.027)	(0.026)
IVOL	0.012*	0.060***	0.058***	0.061***
	(0.006)	(0.006)	(0.006)	(0.006)
E/P	-0.114***	-0.088***	-0.091***	-0.084***
	(0.014)	(0.010)	(0.010)	(0.010)
BM	-0.035***	0.027***	0.025***	0.030***
	(0.009)	(0.008)	(0.008)	(0.008)
SIZE	-0.196***	-0.060***	-0.067***	-0.054**
	(0.025)	(0.022)	(0.022)	(0.023)
PROF	0.044***	0.024***	0.025***	0.021**
	(0.011)	(0.009)	(0.009)	(0.009)
INV	-0.003	-0.018***	-0.017***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
LEV	-0.008	0.026***	0.025***	0.027***
	(0.009)	(0.008)	(0.008)	(0.008)
Firm FE	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes
N	181055	181055	181055	181055
R-sq	0.124	0.352	0.346	0.358

Note: This table examine how higher-order sentiment (Higher-order Sentiment) affects the retail order flow. Column (1) we regress total retail order flow imbalance (Retail Order Imbalance) on Higher-order Sentiment while controlling the First-order 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. TURN) 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, Lag. TURN and Fraction HOB. Standard errors double clustered at firm and yearwk level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A.5. Model Comparison Correlation and Accuracy

	Gemini 2.0 Flash	
	Sentiment Correlation	HOB Classification Accuracy
	(1)	(2)
	Panel A: Comparison with GPT	
GPT 5 Mini	0.70	81.5%
N	5000	10000
	Panel B: Comparison with Human	
Human		81.2%
N		1000

Note: This table reports robustness checks using different LLMs. In Panel A, we apply the same prompts to Gemini 2.0 Flash (our benchmark model), and GPT-5-mini to examine 2500 random FOB posts and 2500 random HOB posts. In Panel B, we randomly select 500 FOB posts and 500 HOB posts, and manually assign whether the posts is an HOB posts or not, then compare the classification with our Benchmark model. Columns (1) examines the correlation between the benchmark model and the alternative model in measuring sentiment attributed to others, treated as continuous variables. Column (2) compares the models' classifications to assess whether a post is identified as a higher-order belief (HOB) message.

Table A.6: Robustness Check for Different LLMs

Dep Var:	(1)	(2) Fraction HOB	(3)	(4)	(5) Higher-order Sentiment	(6)	(7)	(8) Retail Order Imbalance	(9)
	(GPT)	(Gemini)	(Gemini)	(GPT)	(GPT)	(Gemini)			
Higher-order Sentiment (GPT)	-0.179***	-0.199***							
	(0.028)	(0.028)							
Higher-order Sentiment			-0.200***						
			(0.029)						
Higher-order Sentiment Diff			-0.008						
			(0.026)						
Relative Sentiment (GPT)							-0.009***	-0.008***	
							(0.002)	(0.002)	
Relative Sentiment									-0.008***
									(0.002)
Fraction HOB (GPT)				-0.191***				-0.471***	
				(0.029)				(0.029)	
Fraction HOB					-0.199***	-0.195***	-0.454***		-0.467***
					(0.028)	(0.029)	(0.028)		(0.030)
Fraction HOB Diff						-0.002			0.004***
						(0.003)			(0.002)
First-order Sentiment	0.156***	0.178***	0.179***	0.194***	0.194***	0.195***	0.093***	0.093***	0.093***
	(0.030)	(0.031)	(0.031)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Disagreement	-0.811***	-0.850***	-0.851***	-0.681***	-0.682***	-0.682***	0.124***	0.124***	0.124***
	(0.039)	(0.039)	(0.039)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
RET	-0.822***	-0.865***	-0.865***	0.089***	0.089***	0.088***			
	(0.143)	(0.145)	(0.145)	(0.012)	(0.012)	(0.012)			
E/P	0.228***	0.257***	0.257***	0.020***	0.020***	0.021***	-0.113***	-0.114***	-0.114***
	(0.055)	(0.055)	(0.055)	(0.004)	(0.004)	(0.004)	(0.014)	(0.014)	(0.014)
BM	0.050	0.048	0.048	0.001	0.001	0.001	-0.035***	-0.035***	-0.035***
	(0.059)	(0.061)	(0.061)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
SIZE	-0.772***	-0.843***	-0.843***	-0.116***	-0.117***	-0.118***	-0.196***	-0.196***	-0.196***
	(0.209)	(0.212)	(0.212)	(0.015)	(0.015)	(0.015)	(0.025)	(0.025)	(0.025)
PROF	0.219***	0.214***	0.214***	0.001	0.001	0.001	0.044***	0.044***	0.044***
	(0.063)	(0.064)	(0.064)	(0.005)	(0.005)	(0.005)	(0.011)	(0.011)	(0.011)
INV	-0.116***	-0.117***	-0.117***	-0.004	-0.004	-0.004	-0.003	-0.003	-0.003
	(0.042)	(0.042)	(0.042)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
LEV	-0.116	-0.103	-0.103	-0.000	-0.000	-0.001	-0.008	-0.008	-0.008
	(0.081)	(0.083)	(0.083)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
MOM-1M	0.337***	0.326***	0.326***	-0.045***	-0.045***	-0.045***	-0.243***	-0.243***	-0.243***
	(0.091)	(0.092)	(0.092)	(0.008)	(0.008)	(0.008)	(0.026)	(0.026)	(0.026)
IVOL	-0.557***	-0.573***	-0.573***	-0.009***	-0.009***	-0.009***	0.012*	0.012*	0.012*
	(0.034)	(0.034)	(0.034)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
Lag. TURN							0.229***	0.229***	0.229***
							(0.029)	(0.029)	(0.029)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	210053	210053	210053	210053	210053	210053	181055	181055	181055
R-sq	0.196	0.191	0.191	0.185	0.185	0.185	0.124	0.124	0.124

Note: This table reports robustness checks using different LLMs. We first randomly select a sample of 10,000 posts and ask GPT-5-mini to perform the same HOB message classification task as Gemini, and then compute the corresponding sentiment attributed to others. Next, we fit a simple neural network model using Word2Vec embeddings and Gemini's labels as the main features to predict the GPT-5-mini classifications. Higher-order Sentiment (GPT) and Fraction HOB (GPT) represent the higher-order sentiment and fraction of HOB messages derived from the predicted GPT classifications, respectively. Higher-order Sentiment Diff and Fraction HOB Diff represent the differences between Gemini- and GPT-based measures. In columns (1) we test the Fraction HOB (GPT) by using Higher-order Sentiment (GPT). Column (2) we change the dependent variable to Fraction HOB, and Column (3) we replace the independent variable to Higher-order Sentiment but controlling the Higher-order Sentiment Diff. Column (4) to (6) we follow the same procedures to study the impact on Higher-order Sentiment. Column (7) to (9) then changing the dependent variable to Retail Order Imbalance. Control variables include First-order 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. TURN) 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). All variables are winsorized at 1% - 99% level and standardized except MOM-1M, Lag. TURN, RET and Fraction HOB (GPT- and Gemini). * p<0.1, ** p<0.05, *** p<0.01

Table A.7: Robustness for Fixed Effect and Clusters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep Var:	Fraction Hob			Higher-order Sentiment			Retail Order Imbalance		
Relative Sentiment							-0.006***	-0.005**	-0.005*
							(0.002)	(0.002)	(0.003)
Higher-order Sentiment	-0.240***	-0.256***	-0.256***						
	(0.033)	(0.037)	(0.023)						
First-order Sentiment	-0.531***	-0.530***	-0.530***	0.198***	0.199***	0.199***	0.081***	0.081***	0.081***
	(0.038)	(0.039)	(0.023)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)	(0.003)
Disagreement	-1.254***	-1.213***	-1.213***	-0.731***	-0.737***	-0.737***	0.131***	0.123***	0.123***
	(0.050)	(0.052)	(0.023)	(0.009)	(0.008)	(0.006)	(0.008)	(0.008)	(0.006)
Fraction HOB				-0.214***	-0.225***	-0.225***	-0.351***	-0.354***	-0.354***
				(0.030)	(0.033)	(0.020)	(0.025)	(0.025)	(0.023)
RET	-0.154	-0.020	-0.020	0.070***	0.090***	0.090***			
	(0.150)	(0.174)	(0.141)	(0.012)	(0.012)	(0.013)			
E/P	0.350***	0.230***	0.230***	0.004	0.007*	0.007***	-0.114***	-0.114***	-0.114***
	(0.054)	(0.057)	(0.026)	(0.004)	(0.004)	(0.002)	(0.011)	(0.011)	(0.003)
BM	-0.088	0.011	0.011	0.001	0.002	0.002	-0.022***	-0.024***	-0.024***
	(0.062)	(0.064)	(0.024)	(0.004)	(0.003)	(0.002)	(0.006)	(0.006)	(0.002)
SIZE	-1.476***	-1.402***	-1.402***	-0.038***	-0.037***	-0.037***	-0.100***	-0.100***	-0.100***
	(0.117)	(0.120)	(0.032)	(0.006)	(0.006)	(0.003)	(0.007)	(0.007)	(0.003)
PROF	0.829***	0.849***	0.849***	0.010***	0.010**	0.010***	0.021***	0.023***	0.023***
	(0.062)	(0.063)	(0.027)	(0.004)	(0.004)	(0.003)	(0.006)	(0.006)	(0.003)
INV	-0.257***	-0.198***	-0.198***	-0.005*	-0.009***	-0.009***	-0.001	0.002	0.002
	(0.043)	(0.045)	(0.022)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.002)
LEV	0.120	0.131*	0.131***	0.001	0.001	0.001	0.004	0.004	0.004
	(0.075)	(0.078)	(0.023)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)
MOM-1M	0.672***	0.446***	0.446***	-0.062***	-0.043***	-0.043***	-0.302***	-0.242***	-0.242***
	(0.100)	(0.121)	(0.080)	(0.008)	(0.008)	(0.008)	(0.026)	(0.025)	(0.008)
IVOL	-0.772***	-0.683***	-0.683***	-0.011***	-0.010***	-0.010***	0.016***	0.022***	0.022***
	(0.039)	(0.043)	(0.025)	(0.003)	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)
Lag. TURN							0.308***	0.310***	0.310***
							(0.030)	(0.030)	(0.006)
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	210561	210561	210561	210561	210561	210561	181501	181501	181501
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 Higher-order Sentiment as the dependent variable. Columns (7) to (9) repeat the analysis using Retail Order Imbalance as the dependent variable. Control variables include First-order Sentiment, 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. TURN) 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). All variables are winsorized at 1% - 99% level and standardized except MOM-1M, Lag. TURN, RET and Fraction HOB. * p<0.1, **p<0.05, ***p<0.01

Table A.8: Robustness for N HOB posts >= 3

Dep Var:	(1) Higher-order Sentiment	(2) Retail order Imbalance	(3) Non-Retail Order Imbalance	(4) RET T+1	(5) RET T+1 to T+3
Relative Sentiment		-0.009*	0.010**	0.098***	0.247***
		(0.005)	(0.005)	(0.033)	(0.058)
First-order Sentiment	0.186***	0.085***	-0.077***	0.012	0.080
	(0.006)	(0.006)	(0.006)	(0.038)	(0.068)
Disagreement	-0.703***	0.234***	-0.268***	-0.479***	-0.532***
	(0.011)	(0.018)	(0.018)	(0.099)	(0.181)
Fraction HOB	0.001	-0.709***	0.591***	0.414	1.123**
	(0.035)	(0.047)	(0.048)	(0.282)	(0.464)
RET	0.046***			-0.042***	-0.074***
	(0.009)			(0.006)	(0.008)
E/P	0.016***	-0.141***	0.157***	-0.072	-0.217
	(0.004)	(0.017)	(0.018)	(0.291)	(0.738)
BM	0.001	-0.027**	0.020*	-0.099	-0.282
	(0.004)	(0.012)	(0.012)	(0.293)	(0.743)
SIZE	-0.106***	-0.237***	0.268***	-0.849***	-2.230***
	(0.014)	(0.030)	(0.032)	(0.148)	(0.329)
PROF	-0.002	0.055***	-0.043***	0.012	-0.035
	(0.005)	(0.013)	(0.013)	(0.051)	(0.129)
INV	0.001	-0.010	0.019**	0.002	0.020
	(0.003)	(0.009)	(0.009)	(0.038)	(0.097)
LEV	0.005	-0.008	-0.006	-0.123**	-0.311***
	(0.006)	(0.011)	(0.012)	(0.049)	(0.119)
MOM-1M	-0.028***	-0.190***	0.167***		
	(0.007)	(0.027)	(0.022)		
IVOL	-0.002	0.003	-0.032***	-0.048	-0.204**
	(0.002)	(0.007)	(0.006)	(0.041)	(0.088)
Lag. TURN		0.158***	-0.343***	-0.100	-0.285
		(0.026)	(0.025)	(0.131)	(0.221)
Firm FE	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes
N	102510	91592	89641	102510	102510
R-sq	0.321	0.167	0.286	0.151	0.207

Note: This table reports robustness tests restricting the sample to firm-week observations with at least 3 higher order belief message coverage (N HOB posts >= 3). This restriction removes approximately 50% of baseline sample. Column (1) replicates the specification in last column of Table 3. Column (2) examines the retail order imbalance using the specification from the last column of Table 4. Column (3) studies the non-retail order imbalance using the specification in last column of Table 5. Columns (4) and (5) examines whether relative sentiment predicts future excess returns including next week returns (RET T+1) and next 3 weeks cumulative returns (RET T+1 to T+3), respectively. Control variables include First-order Sentiment, 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. TURN) 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). All variables are winsorized at 1% - 99% level and standardized except MOM-1M, Lag. TURN, RET and Fraction HOB. * p<0.1, ** p<0.05, *** p<0.01

Table A.9: Robustness for Rationalize Current and Form Expectation Together

Dep Var:	(1) Fraction HOB	(2) Higher-order Sentiment	(3) Retail order Imbalance	(4) Non-Retail Order Imbalance	(5) RET T+1	(6) RET T+1 to T+3
Relative Sentiment			-0.008***	0.019***	0.041***	0.095***
			(0.002)	(0.002)	(0.013)	(0.022)
Higher-order Sentiment	-1.241***					
	(0.046)					
First-order Sentiment	1.617***	0.247***	0.064***	-0.050***	-0.016	-0.007
	(0.058)	(0.005)	(0.003)	(0.003)	(0.014)	(0.026)
Disagreement	0.205***	-0.554***	0.111***	-0.120***	-0.176***	-0.300***
	(0.054)	(0.009)	(0.006)	(0.007)	(0.035)	(0.059)
Fraction HOB		-0.463***	-0.084***	0.025**	-0.094	-0.322**
		(0.016)	(0.014)	(0.012)	(0.074)	(0.130)
RET	-4.842***	0.359***			-0.035***	-0.059***
	(0.230)	(0.013)			(0.005)	(0.007)
E/P	0.352***	0.014***	-0.090***	0.123***	0.135	0.296
	(0.083)	(0.004)	(0.012)	(0.012)	(0.113)	(0.301)
BM	0.045	-0.004	-0.038***	0.032***	-0.627***	-1.815***
	(0.087)	(0.004)	(0.008)	(0.008)	(0.092)	(0.214)
SIZE	0.797***	-0.066***	-0.184***	0.211***	0.130	0.256
	(0.300)	(0.013)	(0.023)	(0.022)	(0.112)	(0.304)
PROF	0.034	0.002	0.034***	-0.026***	-0.046	-0.072
	(0.106)	(0.005)	(0.009)	(0.009)	(0.031)	(0.077)
INV	0.031	-0.005	0.001	0.008*	0.000	0.018
	(0.063)	(0.003)	(0.005)	(0.005)	(0.021)	(0.054)
LEV	-0.075	-0.003	-0.005	-0.012	-0.090***	-0.206***
	(0.126)	(0.005)	(0.007)	(0.008)	(0.028)	(0.073)
MOM-1M	0.092	0.016**	-0.276***	0.235***		
	(0.140)	(0.007)	(0.024)	(0.019)		
IVOL	-0.262***	-0.015***	0.017***	-0.046***	-0.038	-0.137**
	(0.050)	(0.002)	(0.006)	(0.005)	(0.028)	(0.059)
Lag. TURN			0.337***	-0.718***	-0.201	-0.466**
			(0.037)	(0.035)	(0.124)	(0.218)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Yearwk FE	Yes	Yes	Yes	Yes	Yes	Yes
N	307511	307511	262231	256163	307511	307511
R-sq	0.139	0.208	0.105	0.228	0.141	0.183

Note: This table reports robustness tests for all post which attribute to others including both rationalize current/past or form expectation. This condition increases approximately 50% of baseline sample. Column (1) replicates the specification in last column of Table 2. Column (2) replicates the specification in last column of Table 3. Column (3) examines the retail order imbalance using the specification from the last column of Table 4. Column (4) studies the non-retail order imbalance using the specification in last column of Table 5. Columns (5) and (6) examines whether relative sentiment predicts future excess returns including next week returns (RET T+1) and next 3 weeks cumulative returns (RET T+1 to T+3), respectively. Control variables include First-order Sentiment, 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. TURN) 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). All variables are winsorized at 1% - 99% level and standardized except MOM-1M, Lag. TURN, RET and Fraction HOB. * p<0.1, ** p<0.05, *** p<0.01