Disagreement on the Horizon *

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Abstract

Using data from The Motley Fool's social prediction platform, CAPS, we find substantial differences in stock predictions across investment horizon. Short-horizon investors react more than twice as much as long-horizon investors to earnings surprises and technical view events. Around acquisition rumors, short- and long-horizon investors update in opposite directions about the target: short-term investors become more optimistic, while long-term investors become more pessimistic. Motivated by these findings, we develop a firm-day measure of *horizon disagreement*, spanning from 2006 to 2022, and find it relates significantly to abnormal trading. Additionally, the disagreement-trading relation strengthens on earnings announcement days, providing new evidence on the role of model disagreement.

Keywords: Social finance, social media, investment horizon, disagreement, trading

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1 Introduction

In financial markets, agents are often compelled to choose between taking a short-term versus a long-term perspective. For example, Dessaint, Foucault, and Frésard (2021) shows how the abundance of short-term data can lead analysts to neglect long-term forecasts, potentially shortening investors' horizons.[1] Despite the longstanding attention to investor horizons and corporate decisions in the literature (e.g., Froot, Perold, and Stein, 1992), little is known empirically about how different investor horizons contribute to disagreement among investors and trading in financial markets. This is an important gap given the central role that investor horizon plays in theoretical models of disagreement (e.g., see Hong and Stein, 1999; Kondor, 2012; Banerjee, Davis, and Gondhi, 2018).

In this paper, we explicitly measure investors' horizons using prediction-level data from The Motley Fool's social prediction platform, CAPS. Our empirical tests show that short-horizon investors update differently than long-horizon investors around important firm events, such as earnings announcements. We also construct a measure of *horizon disagreement* that captures the degree to which CAPS users with different horizons disagree about the same stock on the same day. Horizon disagreement has a strong relationship with contemporaneous and next-day abnormal trading volume, especially on earnings announcement days.

A key advantage of the CAPS platform is that we observe horizons at the prediction level (i.e., varying by user-stock-date). Furthermore, we observe the user's sentiment associated with each prediction. Unlike existing settings in which investors' horizons have been measured in the literature—e.g., based on portfolio turnover or churn of institutions (Bushee, 1998; Gaspar, Massa, and Matos, 2005; Yan and Zhang, 2009)—we observe

[1]Such a shortening of investors' horizons is potentially concerning, given that firms' horizons matter for corporate decisions (Edmans, Goldstein, and Jiang, 2012; Dessaint, Foucault, Frésard, and Matray, 2019; Foucault and Fresard, 2014), and shorter horizons might change firms' incentives to make valuable long term corporate investments, such as patenting, R&D or ESG (Bushee, 1998; Starks, Venkat, and Zhu, 2017; Agarwal, Vashishtha, and Venkatachalam, 2018).

information on investors' horizons *and* sentiment at the prediction level. This unique feature of our data enables us to construct separate sentiment evaluations of a firm's stock by short- versus long-term investors, providing novel measurement of and insight into investor disagreement based on differences of investment models (e.g., Kandel and Pearson, 1995).

Our sample consists of 3.1 million CAPS predictions made by 137,000 users regarding the 1,333 most frequently discussed stocks on the platform from 2006 to 2022. For each prediction, a user selects a horizon, choosing from 3-week, 3-month, 1-year, 3-year, 5-year or unspecified, and each prediction is sentiment-stamped based on whether the user believes the stock will *outperform* or *underperform* the S&P500 index. Importantly, each user can only have one prediction outstanding about a given stock at any given time. To update either the sentiment or the horizon of the prediction, a user must close out the existing prediction and start a new one. Optionally, users can supply a pitch—a short textual description supporting their prediction. We have 420,000 pitches in our dataset, across all investment horizons.

Using these pitches, we first validate that users who select shorter horizons indeed have a short-term perspective. We perform two complementary validation tests. First, we summarize the most frequently occurring bigrams in the pitch text. The bigrams "short term" and "long term" are in the top 10 bigrams across all pitches, with "short term" being the most common bigram associated with shorter horizons and "long term" being the most common bigram associated with longer horizons. Second, beyond counting relative frequencies of bigrams, we develop "short term" and "long term" topic dictionaries by seeding a *word2vec* algorithm with the top short-term versus long-term words similar to the approach in Li, Mai, Shen, and Yan (2021). Short-horizon pitches load much more strongly on the short-term topic relative to the long-term topic, unlike the long-horizon pitches. This pattern holds even when we compare different-horizon predictions made by the same user using regressions with user, date, and stock fixed effects. In addition to these textual validation tests, we also find that short-horizon predictions become substantially less optimistic than long-horizon predictions around the onset of the Covid-19 pandemic in 2020.

Another important difference across investors' horizons that emerges from the content analysis of pitches is that short horizon predictions are more likely to use technical analysis terms like *moving average*, while long-horizon predictions are more likely to use fundamental analysis terms like *balance sheet* and *cash flow*. We perform another topic analysis using *word2vec* to examine the usage of technical versus fundamental terms across pitches with different horizons. As with the short-term versus long-term language, we find that the tilt towards technical language in shorter-horizon predictions holds even in a regression setting that employs user, stock, and date fixed effects. Because horizons are related to the user's investment strategy (technical versus fundamental), our later analysis of disagreement controls for disagreement across different investment approaches (using an established measure from StockTwits, Cookson and Niessner, 2020).

We next examine whether users with different horizons update their sentiment differently around important financial events. We focus on three major types of events identified by the news data provider RavenPack: earnings announcements, technical view events, and rumors that the firm is an acquisition target. This analysis constitutes our core findings, showing systematic differences in sentiment updating by horizon.

RavenPack separately delineates earnings announcements based on whether the earnings surprise is positive or negative. Our first main result is that users on CAPS update the sentiment of their predictions in the direction of the earnings surprise, controlling for news, recent volatility, recent returns, and a suite of fixed effects (user, stock, and date). For three-week horizons, a positive earnings announcement is associated with a three percentage point higher likelihood of an 'outperform' prediction, or about 6.2% of a standard deviation in sentiment. However, the size of the sentiment updates differs across horizons: short-horizon predictions are associated with much larger sentiment updates than longer horizon predictions, for both positive and negative earnings surprises. For example, a negative earnings surprise is associated with a 4.2 percentage point increase in the likelihood of an 'underperform' prediction at the three-week horizon, a reaction that is 5.2 *times* the sentiment update for predictions made with a five-year horizon. This finding holds using within-user, within-stock, and within-date variation.

We next analyze changes in sentiment around technical view events from RavenPack. Ravenpack distinguishes between bearish and bullish technical view events—a bullish event indicates that there is news saying that technical indicators predict the stock's price to increase, whereas a bearish event predicts a decrease. We again find that short horizon investors are more responsive in their sentiment updates to technical news than long-horizon investors. This result corroborates our earlier finding that short-horizon investors are more likely to use technical language in their pitches. As with the earnings announcement news, these results hold within stock, date, and user.

Lastly, we examine changes in sentiment on days when a firm is rumored to be an acquisition target. Disagreement across horizons is natural in this setting since short-horizon predictions are more likely to expire before the merger outcome is known, whereas long-horizon predictions are more likely to expire after the merger either completes or falls through. Consistent with the possibility of horizon-based disagreement around merger rumors, we find that short-horizon predictions and long-horizon predictions update *in different directions*. Short-horizon predictions become more optimistic about the target on the acquisition rumor date, whereas long-horizon predictions become more pessimistic.

Motivated by these findings around important financial events, we next construct a firm-day level measure of *horizon disagreement*, which captures the degree to which predictions made at different horizons about the same stock on the same day tend to be different from one another. We find that horizon disagreement is significantly correlated with abnormal trading volume, even after controlling for recent returns, volatility, lagged abnormal trading volume, contemporaneous media coverage, and stock and day fixed effects. Beyond establishing a contemporaneous relation between horizon disagreement and trading volume, we also find that there is significantly more abnormal trading volume on day t that is related to horizon disagreement on day $t-1$, partly assuaging reverse causality concerns.

In our final analysis, we examine how the relationship between horizon disagreement and trading evolves around important financial events. We find that the relation between horizon disagreement and abnormal trading volume *triples* on earnings announcement days, but it does not meaningfully increase around acquisition rumors or technical view events. A natural interpretation of the findings is that horizon disagreement around earnings news is driven by differential interpretation of the public signal (Kandel and Pearson, 1995), whereas horizon disagreement around technical view events and acquisition rumors reflects investors with different horizons conditioning on different pieces of information. For example, short horizon investors are more likely to use technical language and thus could be more likely to update their sentiment due to technical news. Additionally, due to their shorter horizon, short-horizon investors may focus more on details related to merger arbitrage, a short-horizon strategy. These findings provide a novel insight into the nature of how information surrounding these different events is processed.

In this paper, we make several contributions to the literature on disagreement, investor horizons, and the literature on social media. First, the literature on disagreement has long been concerned with whether disagreement among investors is mostly driven by information differences (Hong and Stein, 1999, 2007) or model differences that either affect information collection (Cookson, Engelberg, and Mullins, 2023) or lead to differential interpretation of public signals (Kandel and Pearson, 1995; Banerjee and Kremer, 2010; Li, Maug, and Schwartz-Ziv, 2022). From a theoretical standpoint, disagreement models often posit that investors differ in their investment horizons (Kondor, 2012; Banerjee, Davis, and Gondhi, 2018) as an important aspect of model disagreement. Yet, to date, there has not been an explicit analysis of disagreement across horizons, despite significant attention to other aspects of model disagreement—partisanship (Cookson, Engelberg, and Mullins, 2020), culture and language (Chang, Hong, Tiedens, Wang, and Zhao, 2013), investment philosophies (Cookson and Niessner, 2020), and geography (Gerken and Painter, 2023). Our explicit examination of horizon-based disagreement complements this research by empirically examining a new aspect of model disagreement. Moreover, to the best of our knowledge, we are the first to show direct evidence that an important theoretical construct in disagreement models, investor horizons, is an empirically relevant and important aspect of investor disagreement.

Second, our findings and approach contribute to the literature on investor horizons. In this literature, researchers have been primarily focused on understanding the role of investor *composition* across horizons and whether a more short-termist investor base biases decisions toward more short term projects, e.g., see the cases of R&D expenditures, governance, and ESG investments (Bushee, 1998; Derrien, Kecskés, and Thesmar, 2013; Starks, Venkat, and Zhu, 2017). Much of this literature focuses on institutional investors, proxying for short- versus long-term investor horizons using portfolio turnover or churn (Gaspar, Massa, and Matos, 2005; Yan and Zhang, 2009). Other papers have studied investor horizons in the context of VC investors and CEOs, who have limited horizons based on contract design (Barrot, 2017; Cziraki and Groen-Xu, 2020; Agarwal, Cao, Huang, and Kim, 2023). Within this agenda, recent research asks whether abundant short-term information affects the incentives of financial analysts to invest in the quality of short-term versus long-term forecasts (Dessaint, Foucault, and Frésard, 2021) and if this has corresponding effects on corporate investment (Dessaint, Foucault, and Frésard, 2023). This research emphasizes the importance of forecasting horizons. Even relative to the research on forecast horizons of analysts, our ability to directly observe the investor's chosen horizon is unique, and it allows us to directly study sentiment differences by horizon.[2] For

[2]Unlike CAPS predictions, which have a single specified horizon reflecting the user's outlook, financial analysts make multiple simultaneous forecasts for a set of common horizons; thus, differences across analyst horizon-level forecasts are unlikely to proxy for disagreement among investors with different investment horizons, an important contrast with CAPS prediction horizons.

example, our micro-level evidence on how investors with different horizons react to different corporate events is a new and useful contribution to the understanding of how investors process information differently depending on their investment horizon.

Finally, our research joins a recent stream of literature that gains insights from the rise of financial social media platforms. Much of this research has been conducted using StockTwits, Twitter, Seeking Alpha, and Reddit (Chen, De, Hu, and Hwang, 2014; Giannini, Irvine, and Shu, 2019; Cookson and Niessner, 2020; Müller, Pan, and Schwarz, 2023; Dim, 2023; Cookson, Lu, Mullins, and Niessner, 2024). Relative to these platforms, CAPS has been mostly overlooked by the research community, which is striking because The Motley Fool is one of the oldest financial social media platforms with significant activity on CAPS going back to 2006, and its data features are rich, complementing information from other social platforms.[3] In this respect, our research using data from CAPS complements Cassella, Dim, and Karimli (2023) who use predictions on CAPS to show evidence of optimism shifting (i.e., issuing the same prediction, but at a longer horizon) in the presence of disconfirming news, which allows users to maintain their optimism even when they cannot avoid information that contrasts with their priors. Our evidence on the content of investor horizons, their updates and differences across horizons for important firm events, and the construction of the horizon disagreement measure contribute unique insights while using CAPS as a lens (Cookson, Mullins, and Niessner, 2024) to think about the broader market phenomenon of horizon-based disagreement.

[3] Apart from recent interest in CAPS, an earlier paper by Avery, Chevalier, and Zeckhauser (2016) shows that aggregated sentiment from CAPS is predictive of future outcomes, akin to Chen, De, Hu, and Hwang (2014)'s findings using Seeking Alpha.

2 Setting and Data

In this section, we provide an overview of the Motley Fool's CAPS platform and detail the dataset we have extracted from it. We also highlight the important characteristics of the predictions made on the platform.

2.1 Motley Fool's CAPS Platform

CAPS (https://caps.fool.com/) is a social finance forum for stock predictions hosted by The Motley Fool social media platform. CAPS is free of charge to anyone who wants to make predictions or look up other people's predictions about the future performance of individual stocks relative to the S&P500 index. Figure 1, Panel A presents a screenshot of the way users see the homepage, which displays recent forecasts, recent pitches, the best and the worst performers over the last day and the option for the user to rate a stock. CAPS predictions are only possible for eligible tickers, which have sufficient daily trading volume ($50,000 or more in the preceding day and quarter) and a sufficiently high price (> $1.50). These restrictions aim to eliminate predictions on very illiquid and microcap stocks.

When CAPS users make predictions on the platform about the stock, they see the current price, the current return relative to the previous market close, and the stock exchange where the stock is trading. Figure 1, Panel B illustrates how this information is presented for Tesla stock. A forecast on CAPS is a statement about whether the stock will *outperform* or *underperform* the S&P500, and importantly for our study, the prediction's *horizon*—three-week, three-month, one-year, three-year, five-year or unspecified. Most users actively choose a horizon when making a CAPS prediction, suggesting that the horizon is relevant to their evaluation of the stock. The prediction-specific horizon is a unique feature of CAPS relative to other financial social media platforms. For example, investors on StockTwits can indicate their investment horizon, but it is not stock-specific.

Users on CAPS also have an option to write a short pitch justifying their prediction. Although the pitch is not required, a large sample of predictions have pitches that can provide insights into the forecaster's thought process. Figure 2 displays examples of pitches for predictions with different horizons.

Another distinguishing feature of CAPS is that users may have at most one *active* prediction per stock. Users can make forecasts about multiple stocks at the same time, but new predictions about a given stock must replace old ones, by canceling the original prediction and initiating the new one. CAPS users are incentivized to make good predictions because their predictions factor into their ranking on the platform. Although there are no explicit monetary rewards to being highly ranked, the top forecasters are celebrated on the platform. Forecast performance is evaluated on a daily basis. This evaluation system nudges users to select the forecast and horizon based on their beliefs rather than to engage in strategic attempts to game the evaluation system.

2.2 CAPS Data

Our full sample contains 6.58 million predictions initiated between April 2006 and December 2022. These predictions were made by 199,228 individuals regarding 12,434 stocks. After the match with data from Center for Research in Security Prices (CRSP) and keeping predictions on ordinary common shares (share codes 10, 11, 12), we are left with 4.23 million predictions. Further, to focus on a sample with sufficient variation at the user and stock level, we retain predictions made by users with at least two predictions, and focus on stocks that ranked in the top 20% by the number of predictions during our time period. These filters yield a final sample of roughly 3.1 million predictions initiated by 137,750 users about 1,333 stocks. For each prediction, we observe the prediction date, the stock ticker, the prediction horizon, and, where available, the written text of the pitch in support of the prediction. When users make predictions, their two options are either "outperform" or "underperform." To capture a prediction's sentiment, we code the sentiment of "outperform" predictions as 1 and of "underperform" predictions as -1, consistent with the handling of bullish versus bearish messages in other settings (e.g., Antweiler and Frank, 2004).

2.2.1 CAPS user characteristics

Figure 3 presents additional information on CAPS users, based on their posting behavior and profile information. Panel A presents the distribution of investors' tenure on CAPS and on another popular social media platform – StockTwits. Nearly half of CAPS users spend less than a month on the platform based on the time between the first and last prediction in our sample. This distribution of survival times on the CAPS platform is comparable to StockTwits. If anything, a greater fraction of CAPS users in our sample continue to make predictions on the platform for more than 5 years. Panel B presents the empirical distribution of the users' self-reported investment experience and risk tolerance, extracted from their profile. The vast majority of CAPS users exhibit medium, medium high or high risk tolerance, while user experience varies more, with significant fractions of users claiming to be low, medium and high experience.

2.2.2 CAPS Summary statistics

Table 1 summarizes our main sample. Panel A presents horizon-level summary statistics on predictions, including the average sentiment and the number of predictions, pitches, unique users, and unique stocks. Each horizon has more than 240,000 predictions, but there are differences in their relative frequencies. The three-week and the three-month forecasts are least common, comprising 5.7% and 8.6% of predictions, respectively, whereas the five-year forecast is the most-common (47% of predictions). Predictions with an unspecified horizon make up only 14.4% of the predictions and 7.7% of the pitches. Panel

A of Figure 4 shows the fluctuation in the share of short horizon predictions over time, which is relatively constant at around 0.1 for most of the time period.

The average sentiment is positive across all horizons, indicating that "outperform" predictions are more common than "underperform" predictions. Furthermore, predictions with longer horizons have higher average sentiment: the average sentiment for the short horizon predictions (three-week and three-month) ranges from 0.3 to 0.442, whereas sentiment for long horizon predictions (one-year to five-year) ranges from 0.613 to 0.819. In addition, Panel A presents statistics on the number of pitches, number of unique users, and number of unique stocks discussed at each horizon. These are distributed similarly to the number of predictions.

In addition, Panel A shows that the bullishness of beliefs expressed on CAPS tends to increase with the expectation horizon. This finding is consistent with the recent evidence of an upward-sloping term structure of optimism among financial analysts and macroeconomic forecasters (Cassella, Golez, Gulen, and Kelly, 2021, 2023), and helps to validate that the CAPS prediction horizons are meaningful and align with patterns about the term structure of expectations in other domains.

Panel B of Figure 4 displays another validation of the empirical content of the CAPS horizons. The figure displays the time series difference between the average sentiment of long- and short-horizon forecasts. Although long horizon predictions are more bullish throughout the sample period, they become markedly more bullish than short horizon predictions during the onset of the Covid-19 pandemic in early 2020, and similarly increase in their bullishness around the high inflation period and rate hikes during 2022. These significant shifts in long- versus short-horizon sentiment presage our firm event tests, which show important differences in how predictions with different horizons react to important firm events.

Panel B of Table 1 presents statistics on the sample coverage and depth at the user and stock level. The average number of predictions per user is 22.6 (median is 6). In our sample, users tend not to focus on one stock at a time, making predictions on an average of 18.1 distinct stocks (median of 6). Both of these distributions are right skewed: 10% of users make more than 43 predictions within our sample. From the standpoint of building stock-level measures, the average stock received 2,336 predictions over the full sample (median of 1,396). The distribution is somewhat right skewed, with 10% of the stocks receiving an average of 4,345 or more predictions.

Beyond the user- and stock-level information, there is substantial within-user variation in the prediction horizons. Specifically, the average user makes forecasts with 2.5 different horizons during their tenure on CAPS (with the maximum possible being 6). Appendix Figure A1 illustrates this within-user variation by reporting the R^2 from regressing dummy variables for each horizon choice on user fixed effects, stock fixed effects, date fixed effects and stock by date fixed effects. By this R^2 metric, user fixed effects explain at most 50% of the variation in horizon choice; stock-day fixed effects leave a similar amount of residual variation. We explicitly rely on this within-user, within-stock and within-day variation in our tests of sentiment updates around important financial events.

Panel C of Table 1 summarizes the sentiment of the predictions on CAPS. The average sentiment over the full sample is 0.676, while the average user (stock) has an average sentiment of 0.802 (0.661). These numbers indicate that sentiment expressed on CAPS is generally very bullish, in line with findings in the recent literature involving data from other social finance platforms (Cookson, Engelberg, and Mullins, 2023; Dim, 2023; Cookson, Lu, Mullins, and Niessner, 2024).

Our main sample described above contains 420,287 predictions with a user-supplied pitch. Panel D of Table 1 summarizes the textual content of these pitches. The pitches tend to be short, with an average of roughly 30 words, comprising 168 characters (medians of 14 words and 81 characters). However, some of the pitches are quite detailed as the distributions of number of characters and words are both right skewed. In particular, 10% of pitches use more than 66 words and more than 365 characters in the pitch. In addition, we compute the polarity, a measure of textual sentiment, for each pitch. On average, the sentiment is positive, indicated by the average polarity of 0.252, similar to the sentiment drawn from the prediction's "outperform" vs "underperform" labels.[4]

Panel E of Table 1 summarizes the characteristics of the stocks in our final sample. For time-varying proxies, we average each characteristic at the stock level before computing the cross-sectional stock characteristics. The average stock has a market capitalization, price, and market beta of $13 billion, $45.8, and 1.25, respectively. There is also substantial cross-sectional variation in the characteristics, indicating a rich heterogeneity in the stocks for which forecasts exist on CAPS.

2.3 CAPS predictions versus other information sources

CAPS predictions have several advantages over other, more traditional, sources of financial information. For example, CAPS users are unlikely to be biased by strategic considerations that distort forecasts of traditional analysts, such as reputational or financial incentives from catering to the firms they cover (e.g., Michaely and Womack, 1999; Lim, 2001; Jackson, 2005). Individuals who make predictions on CAPS are primarily retail investors. They use pseudonyms and do not receive any financial compensation from the firm or the platform. These features enable us to study horizon-dependent beliefs without the concern that the forecasts are not the investors' true beliefs, but also reflect strategic considerations.[5]

While CAPS shares similarities with other investor social platforms like Seeking Alpha and StockTwits, it also has unique features that set it apart. CAPS has similar user populations to other social media platforms, and the signals drawn from CAPS predictions

[4]The textual sentiment of the pitches and "outperform" versus "underperform" labels are also positively correlated, with a correlation coefficient of roughly 0.3.

[5]CAPS predictions may be *behaviorally* biased — e.g., see work by Cassella, Dim, and Karimli (2023) who show how CAPS users maintain optimism when presented with disconfirming information. However, even in the case of behaviorally biased beliefs, the forecasts on CAPS are the true *beliefs* of the forecasters.

convey comparable information. For instance, aggregated sentiment from CAPS has been shown to predict future returns (Avery, Chevalier, and Zeckhauser, 2016), which aligns with evidence from Seeking Alpha (Chen, De, Hu, and Hwang, 2014) and StockTwits (Cookson and Niessner, 2020). However, a distinguishing feature of CAPS is that its predictions typically have a horizon, unlike other investor social platforms. This characteristic is central to our empirical tests. In the following sections, we analyze the empirical and economic content of these prediction horizons.

3 Prediction Horizons

In this section, we examine the properties of CAPS prediction horizons. We begin by studying the language used in pitches and how this language relates to the horizon the CAPS user selected. We further examine how sentiment across different horizons evolves around important financial events, with a particular focus on events where users with short versus long horizons may react differently.

3.1 Language across Horizons

For the subset of predictions that are accompanied by a pitch, we use the textual content to understand the nature of predictions at different horizons. In Figure 5, we show the top ten bigrams by prediction horizon with the bigram "short term" highlighted in blue and the bigram "long term" highlighted in red. Strikingly, "short term" is the most commonly used bigram in the pitches of shorter horizons (e.g., three week and three month). For longer horizons (e.g, one year to five year), the frequency of "short term" declines and "long term" becomes the most common bigram. These relative bigram frequencies validate that the horizons used by CAPS users are consistent with the users' beliefs.

The other bigrams in the top 10 lists highlight another interesting feature of short versus long horizon predictions: short term predictions tend to use terms related to technical analysis (e.g., "moving average" and "day moving"), whereas long-term predictions tend to use fundamental analysis terms more frequently (e.g., "cash flow" and "balance sheet").

While the bigram evidence is visually compelling, it does not speak to whether these differences are statistically significant. We examine these patterns systematically by extending the "long term," "short term,", "fundamental," and "technical" top bigrams into comprehensive dictionaries. To do so, we employ *word2vec* (Mikolov, Sutskever, Chen, Corrado, and Dean, 2013) using an implementation that follows Li, Mai, Shen, and Yan (2021) who conduct a similar exercise by creating dictionaries related to corporate culture. To construct these dictionaries, we seed the topics in the word2vec algorithm using top unigrams and bigrams (e.g., for the "long term" topic, we use "long term, "longrun," and "long haul"), and select the top 100 words and bigrams with the largest similarity to the average vector of seed words. Appendix C describes this analysis in technical detail. Table 2 presents the word dictionaries that result from this procedure.

We next use these dictionaries to quantify how much of each topic is reflected in each pitch. Specifically, for each pitch and for a given topic, we count the number of times each word from the topic's dictionary appears in the pitch and apply the term frequency–inverse document frequency (tf-idf) weights to the word counts. We then sum up these weighted counts and divide the sum by the total number of words in the pitch to obtain the $Topic\ Loading_i$ for pitch i. The term frequency–inverse document frequency (tf-idf) weights account for both the importance of a word in a pitch and how frequently the word occurs in the entire pitch corpus.

To examine how the language in the pitches depends on users' horizon, we estimate the following specification

$$Topic\ Loading_{i(k,t)} = \alpha_i + \nu_k + \gamma_t + \sum_{h \in H} b_h \times \mathbb{1}_{horizon_{i(k,t)}} + \epsilon_{i,k,t} \tag{1}$$

$Topic\ Loading_{i(k,t)}$ is how much pitch i's language overlaps with the specific topic for a pitch made about stock k on day t. In some specifications, we compute differences between topic loadings (i.e., Long term − Short term). $Topic\ Loading_{i(k,t)}$ is normalized to have a standard deviation of 1. $\mathbb{1}_{horizon_{i(k,t)}}$ is an indicator variable for the different horizons in the data: three-month, one-year, three-year, five-year, and unspecified. We omit the three-week category to serve as the baseline. Standard errors are double clustered by stock and day.

Before describing the regression results, we present the topic loadings for short-term versus long-term topics graphically in Figure 6. In Panel A, we plot the average loadings by horizon for the short-term topic in red and for the long-term topic in blue. The short-term topic loadings decrease monotonically as the horizon length increases, with pitches for three-week horizons having three times as many short-term terms than the three-month horizon pitches and almost six times as many as the five-year horizon pitches. The topic loadings on the long-term topic are monotonically increasing with the horizon length. However, the increase in long term loadings is less dramatic than the decrease in short term loadings. Panel B of Figure 6 shows how the difference in the loadings (long term minus short term) changes with the prediction horizon. Consistent with the bigram evidence, the pitches load more on the short-term topic for shorter term horizons and more on the long-term topic for longer term horizons.

In Table 3 we present the regression estimates from equation (1) in which the dependent variable is the difference between long term and short term loadings. In all cases, long-term language increases for longer horizons, and the use of long-term language is meaningfully higher than for the three-week baseline category. Further, echoing the graphical evidence, the estimates in this table show a monotonically increasing loading for longer horizons that is highly statistically significant. In addition, columns 2, 3 and 4 include user, date, and stock fixed effects, showing that the disproportionate use of long-term language for longer horizons holds within user, within a given day, and within a given stock (i.e., it does not just reflect stock-specific or user-specific language or time trends in the sample).

To better understand the differences in investment approaches used by short-term versus long-term investors, we conduct a similar exercise in the use of fundamental versus technical language in the pitches. In the bigram analysis longer horizon pitches tend to use more fundamental language while short horizon pitches tend to use more technical analysis language. Using the word2vec approach, as described above, we construct topics for fundamental analysis and technical analysis in the pitches. Figure 7 suggests graphically that short horizon predictions tend to use more technical language than fundamental language. We estimate a model similar to equation (1), except we put Fundamental minus Technical as the dependent variable. The results in Table 4 confirm that the technical versus fundamental differences are statistically significant, and these estimates highlight that short horizon predictions tend to be more technical whereas long horizon predictions tend to be more fundamentally oriented.

3.2 Prediction Horizons Around News Events

An investor's investment horizon could influence how they update their predictions when new information about a firm arrives. For example, suppose an investor considers a prediction with a five-year horizon. Such a long horizon likely incorporates signals beyond this quarter's earnings news. Thus, we may expect long-horizon predictions to be less sensitive to contemporaneous earnings news than short horizon evaluations, such as a three-week or three-month prediction.

In this section, we consider three firm-specific events that can lead investors to update their predictions: earnings announcements (positive versus negative), technical events (bullish versus bearish), and rumors that the firm in question is the target of a merger. We identify the timing of these events and their sign using the events database by Ravenpack 1.0. For each event type, we estimate a linear probability model specification of the form:

$$Outperform_{i(k,t)}(h) = b_1 Event_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t} \tag{2}$$

where $Outperform_{i(k,t)}$ equals 1 for predictions that stock k will outperform the market and 0 for underperform predictions. We multiply the dependent variable by 100 to give a percentage point interpretation to the estimated coefficients. h denotes the prediction horizon. $\mathbf{X}$ includes dummy variables for one week before and one week after the event, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-25$ to $t-6$), and Volatility ($t-5$ to $t-1$) following the controls employed in Cookson and Niessner (2020). Standard errors are double clustered by stock and day. We only focus on predictions initiated on day t.

3.2.1 Earnings Announcements

First, we examine how investors with different horizons update their predictions in response to the direction of the earnings surprise. To do this, we collect positive earnings announcement and negative earnings announcement events from RavenPack (i.e., Ravenpack categories "earnings-above-expectations" and "earnings-below-expectations"), and estimate equation (2) separately by investment horizon. Since positive earnings announcement and negative earnings announcement events are mutually exclusive, we include both positive and negative earnings announcements in the same specification. The coefficients of interest are those on the earnings announcement indicator variables, which estimate the average sentiment update for investors of the specified horizon to positive or negative earnings news.

Figure 8 displays these point estimates by horizon and direction of the earnings news, with Panel A presenting estimates for positive earnings surprises and Panel B presenting estimates for negative earnings surprises. Overall, CAPS users tend to update their sentiment in the direction of the earnings surprise. However, users with short horizons exhibit significantly greater sensitivity to earnings news. Investors with a three week horizon respond the strongest to signed earnings announcements, whereas investors with three-year or five-year horizons do not update significantly or update with a much smaller estimated magnitude.

We next estimate the regression in equation 2, and present the results in Table 5. For a positive earnings announcement, users with three-week horizons are 3 percentage points more likely to issue an 'outperform' prediction, whereas users with three-year and five-year horizons do not significantly change their sentiment. Similarly, for a negative earnings surprise, users with three-week horizons are 4.2 percentage points more likely to issue an 'underperform' prediction, which is *five times* the sentiment reaction of five-year horizon predictions. These magnitudes are meaningful, reflecting an increase of 6.2% of a standard deviation of sentiment for positive earnings news and a decrease of 8.7% of a standard deviation for negative earnings news (see Appendix Table A5). These specifications control for recent returns and volatility, as well as user, date, and stock fixed effects, which rules out many alternative interpretations of the difference in sentiment reactions by horizon.

3.2.2 Technical View Events

Many of the investment pitches contain keywords that explicitly reference technical analysis strategies. Indeed, the short-horizon pitches tend to use this terminology more than the long-horizon pitches. Given this focus on technical versus fundamental strategies at different horizons, we also examine the degree to which technical events shape sentiment differently at different investment horizons. To accomplish this, we identify the set of "technical" events in RavenPack. Like earnings announcements, RavenPack separately delineates negative technical events (category "technical-view-bearish") from positive technical events (category "technical-view-bullish"). RavenPack describes the bearish (bullish) categories as "Technical analysis indicates the Entity's price will depreciate or lose value (appreciate or gain value)." Since forecasts with short-term horizons load more on the technical topic and forecasts with long-term horizons load more on the fundamental topic, it is natural to expect short-term horizons to react more strongly to technical signals.

To test this, we separately estimate equation (2) for different horizons around positive and negative technical events. Figure 9 presents the estimates for bullish technical events in Panel A and bearish technical events in Panel B. Consistent with the evidence around earnings announcements, CAPS forecasts update positively for positive events and tend to update negatively for negative events. Furthermore, users with short horizons update more strongly than users with long horizons. For bullish technical events, the estimate for users with three-week horizons is 2 to 4 times bigger than the estimate for users with longer horizons (i.e., three to five year horizons). For bearish events, the point estimates for longer horizons flip in sign (albeit being small and marginal in statistical significance). We display the full results based on the specification with controls in the Appendix Tables A8 and A9.

3.2.3 Acquisition Rumors

A third category of events we study is when a firm is rumored to be an acquisition target. Mergers and acquisitions are among the most important corporate transactions, and a rumor that a firm might be acquired represents a major financial event (e.g., Ahern and Sosyura, 2015; Ben-Rephael, Cookson, and Izhakian, 2023). However, given that an M&A rumor (or even announcement) does not guarantee that the merger will complete (e.g., Betton, Eckbo, Thompson, and Thorburn, 2014; Bates and Lemmon, 2003; Cookson, Niessner, and Schiller, 2024), the updates in forecasts around the rumor will partially depend on whether the horizon expires before the merger would complete or after. Given that following a merger announcement the typical time to completion is around a year, shorter horizon predictions are more likely to expire during a period when merger arbitrage strategies are active (Baker and Savaşoglu, 2002), than longer-horizon predictions. Therefore, shorter-horizon predictions are more likely to experience the price-increase around the actual announcement without the potential future price decline due to lack of synergies. Whereas, longer-horizon predictions are more likely to expire after the deal would fall apart, and therefore, should be more likely to consider eventual synergies or integration risks (Hoberg and Phillips, 2018). Thus, M&A rumors is a natural setting in which users with short-horizon predictions and users with long-horizon predictions may respond differently.

To examine sentiment changes by prediction horizon around acquisition rumors we collect (again from RavenPack) events with "acquisition-rumor-acquiree" category, which identify when a firm is the rumored target of an acquisition. Using an indicator variable for acquisition rumor events, we estimate equation (2), following the same format as earnings announcements and technical events. Figure 10 presents the estimates on the sentiment updates by horizon. Consistent with the motivating intuition, short horizon predictions increase their sentiment around acquisition rumors, whereas long-horizon predictions *decrease* their sentiment around these same events. We present the full regression estimates in the Appendix Tables A6 and A7. This evidence is consistent with horizon splitting the sample of users into two different investor types: short-horizon investors who are more naturally interested in merger arbitrage or other strategies that realize during the merger interim period, and long-horizon investors who are evaluating the quality of the combined firm.

4 Horizon Disagreement and Trading

In the prior section, we examined several settings in which sentiment differs across prediction horizons: short-horizon investors update more strongly to both earnings news and technical views than long-horizon investors. In addition, short-horizon investors update positively to acquisition rumors, whereas long-horizon investors update negatively. Although these findings are focused around identifiable market events, they demonstrate a wider phenomenon as our textual evidence shows investors with long versus short prediction horizons use distinct language. This difference may reflect different forecasting considerations— i.e., investors place different weights on financial metrics like cash flows, balance sheet information, and price movements.

Collectively, this analysis suggests that it is fruitful to measure the dispersion of opinions across horizons, or *horizon disagreement*. After all, our results suggest horizon disagreement is pervasive around important financial events. Separately, an analysis of horizon disagreement (and its link to market outcomes like trading volume) is instructive due to the widespread use of horizons in models of investor disagreement. Indeed, horizon disagreement is a core aspect of model disagreement, which is difficult to measure directly (Hong and Stein (2007)). In this section, we construct a daily measure of horizon disagreement from CAPS predictions, and relate it to trading volume in the broader market. This analysis speaks to the relevance of model disagreement in financial markets, but it also serves to illustrate that CAPS predictions proxy for the opinions of the broader market.

4.1 Measuring Horizon Disagreement

To construct our measure of horizon disagreement, we adopt the approach of Cookson and Niessner (2020) who compute the weighted standard deviation of sentiment across investment philosophies on StockTwits (e.g., Value, Growth, Momentum, Fundamental, and Technical). The calculation for horizon disagreement has an important difference from the application to investment philosophies: CAPS users' investment horizons often vary across stocks and time, whereas on StockTwits investment philosophies are declared on the users' profile and is user-specific. As we saw in Tables 3, 4 and 5, this 'dynamic' variation in horizons is meaningful as all our main results hold within user in specifications that include user fixed effects.

Since CAPS users can only have one outstanding prediction for any given stock at a time, and users are evaluated based on the performance of their predictions, new forecasts tend to reflect updates to sentiment. As a result, outstanding predictions on CAPS are more likely to reflect current sentiment of the user than on other financial social media forums where users can easily reiterate their views at any given point in time. This feature also leads new predictions to be relatively sparse, which is why we focus on the top 20% of stocks ever mentioned on CAPS. To construct the disagreement measure, we first calculate *AvgSent* at the horizon-stock-date level by computing the arithmetic average:

$$AvgSent_{k,t,h} = \frac{1}{L}\sum_{l}^{L} Prediction\ Sentiment_{l,k,t,h}, \tag{3}$$

where *Prediction Sentiment* is a forecast-level variable that equals 1 if a user's prediction is 'outperform' and -1 for 'underperform', and L is the number of new predictions about stock k at horizon h on day t.

We construct *Horizon Disagreement* at the stock k by day t level by computing the weighted standard deviation of *AvgSent*:

$$Horizon\ Disagreement_{k,t} = \sqrt{\frac{\sum_{h\in H} w_{k,t,h}\left(AvgSent_{k,t,h} - AvgSent_{k,t}\right)^2}{\frac{N_H-1}{N_H}}}, \tag{4}$$

where k, t and h index stock, day and horizon, respectively. $w_{k,t,h}$ is the fraction of predictions about stock k on day t for horizon h, and N_H is the number of forecast horizons. If there are no predictions for a particular stock-day-horizon, we assume that traders do not wish to buy or sell in the near future. Hence, we normalize disagreement in the no-prediction case to 0, consistent with latent agreement, following the definition in Cookson and Niessner (2020).

Table 6 shows summary statistics of Horizon Disagreement, as well as comparisons to other daily-level measures of disagreement. According to Panel A, Horizon Disagreement has a mean of 0.0215 and a standard deviation of 0.1377. For comparison, Panel A also reports *CAPS disagreement* (i.e., disagreement irrespective of horizon) and within-horizon dispersion of opinion for each horizon. Both of these are computed using a simple standard deviation formula. Interestingly, disagreement across horizon tends to be larger than within-horizon disagreement for any horizon, and it also tends to have a greater spread. On average, horizon disagreement is 72% of the overall disagreement. Therefore, in this setting, horizon disagreement is the most prominent source of differences of opinion.

Panel B presents correlations with disagreement measures drawn from StockTwits, available publicly (Cookson and Niessner, 2023). All of the correlations are modest, but horizon disagreement is more strongly correlated with within-group disagreement on StockTwits—i.e., disagreements among people with the *same* investment philosophy—than it is with cross-group disagreement. That is, horizon disagreement is unlikely to reflect previously studied disagreement among investment philosophies on StockTwits (e.g., that Fundamental investors disagree with Technical investors). Panel C presents these correlations in regression format, delivering the same message. In addition to the correlation, the R-squared values suggest that daily StockTwits disagreement measures explain, at most, 2% of the variation in horizon disagreement.

4.2 Horizon Disagreement and Trading Volume

Next, we relate horizon disagreement to abnormal trading volume. This analysis serves to validate the relevance of the horizon disagreement measure extracted from CAPS for financial markets. For this test, we estimate the following specification:

$$\begin{aligned} AbLogVol_{k,t} &= \alpha_t + \gamma_k + \beta_1 Horizon\ Disagreement_{k,t} \\ &\quad + \beta_2 AbLogVol_{k,t-1} + \beta_3 Media_{k,t} + \gamma Controls_{k,t} + \epsilon_{k,t} \end{aligned} \tag{5}$$

Where $AbLogVol_{k,t}$ is the abnormal log trading volume on date t for firm k. It is calculated as the difference between the log volume on date t and the firm's average log volume from $t - 140$ to $t - 20$ trading days (6-month period, skipping a month). The main coefficient of interest is β_1, the slope on *Horizon Disagreement*. To control for the persistence of trading, all specifications control for $AbLogVol_{k,t-1}$. We also control for recent volatility (days $t - 5$ to $t - 1$) and recent abnormal returns (days $t - 25$ to $t - 6$ and $t - 5$ to $t - 1$), as well as the presence of news with an indicator for whether there is any article on the Dow Jones News Wire on day t about firm k. In addition, some specifications include StockTwits measures of disagreement to evaluate whether horizon disagreement relates to volume beyond day-level disagreement measures studied in prior literature. All specifications include firm and date fixed effects, and the standard errors are double clustered by firm and date.

Table 7 presents the results from estimating this specification. Overall, we find a significant relationship between horizon disagreement and abnormal trading volume. A standard deviation increase in horizon disagreement is associated with approximately 1.6% higher abnormal trading, holding constant recent returns, volatility, contemporaneous news coverage and accounting for the persistence of trading. This relationship between horizon disagreement and trading volume persists even after we control for the overall disagreement among StockTwits investors, as well as the within-group and across-group components of the disagreement on StockTwits. Interestingly, the coefficient on horizon disagreement is smaller in magnitude than the coefficient on the overall disagreement from StockTwits, and it is more similar in magnitude to cross-group disagreement than it is to within-group disagreement. This finding suggests that model-based disagreement, reflected in the choice of different prediction horizons, bears a weaker connection to trading than information-based disagreement proxied for by disagreement within investor philosophies.

One concern with establishing the contemporaneous relationship is reverse causality: that horizon disagreement on day t could be driven by abnormal trading volume on day t rather than the other way around. To address this issue, we relate day t abnormal trading to day $t-1$ horizon disagreement in column (5). Although the magnitude is a third of the contemporaneous relationship, the relationship between lagged horizon disagreement and abnormal trading volume is strongly statistically significant.

4.3 Disagreement around Information Events

Given our analysis of sentiment differences across prediction horizons for earnings announcements, technical view events, and acquisition rumors in Section 3, it is natural to examine whether horizon disagreement has a stronger relationship to trading volume around these events, than during other time periods. To examine this, we estimate equation (5), but augmented with terms that interact horizon disagreement with the event day (as well as one week prior and one week after).

Table 8 presents the results from estimating these specifications around the three event types we evaluated in in Section 3. For earnings announcements (columns 1 and 2), we find that horizon disagreement has a much stronger relation to abnormal trading on the earnings announcement day compared to other days. Specifically, the coefficient on the interaction term between horizon disagreement and earnings announcement day (0.030) is twice as big as the baseline coefficient estimate on horizon disagreement. This implies that the connection between horizon disagreement and trading *triples* on the earnings announcement day. In column 2, we control for disagreement measures from StockTwits and their interaction with the announcement days. Neither StockTwits measure exhibits the same amplified relation to trading on the earnings announcement day, nor does controlling for StockTwits disagreement explain the amplification of horizon disagreement's relationship to trading. Figure 11 illustrates this result graphically.

Examining other two event types in columns 3 through 6, we do not see the same kind of amplification of the relation between horizon disagreement and abnormal trading volume as with earnings announcements. For technical view event days, the magnitudes on the interaction term between horizon disagreement and the technical view event day are much smaller than for earnings announcements (0.8% and -1.0% versus 3.0% and 2.2%), and the sign depends on whether StockTwits disagreement is included as a control. For acquisition rumor days, there is a small and insignificant interaction term. That is, although horizon disagreement around these events still exhibits a robust relation to abnormal trading volume (coefficient on the main effect *Horizon Disagreement* is statistically significant), the relation does not seem to increase relative to other trading days. To be clear, as there is more horizon disagreement around these events, there is likely more trading volume (Figures 8, 9, and 10), even though the relationship between disagreement and trading volume does not itself strengthen.

Summarizing the results around different event types, the intensification of trading around earnings announcements is consistent with the view in the literature that updates around earnings news reflect differential interpretation of a public signal (Kandel and Pearson, 1995). By contrast, different sentiment around technical view events and acquisition rumor events more likely reflects differences in the kinds of information relevant to a specific investment strategy—e.g., short-horizon investors who more likely employ technical strategy are more likely to pay attention to technical view events than long-horizon investors with fundamental strategies.

5 Conclusion

There is a longstanding interest in understanding the impacts of investor horizons on investment decisions (e.g., see early work by Froot, Perold, and Stein, 1992), and investor horizon differences have been posited as a source of model disagreement (Kondor, 2012; Banerjee, Davis, and Gondhi, 2018). Nevertheless, previous work lacks an explicit, broad-market evaluation of the importance of investor horizons.

Our measurement of investor horizons from predictions made on The Motley Fool's prediction platform CAPS helps to fill this gap. Not only do we show that user-supplied horizons reflect different approaches to evaluating stocks—short term versus long term, technical versus fundamental—but we also find that short-horizon predictions differ significantly in their reaction to important financial events—earnings announcements, technical view events, and acquisition rumors. Building on our findings, which reveal disagreements across horizons, we construct a firm-day measure of *horizon disagreement* that quantifies the degree to which short- and long-term investors make different predictions about the same stock on the same day. We find this measure relates strongly to abnormal trading, especially on earnings announcement days.

Our study contributes to a broader research agenda that makes use of unique features from investor social media platforms to provide a lens into the functioning of financial markets. As social platforms host more activity, we see great potential to observe other important aspects of investor and corporate decisions through their interactions online. We hope to see more of this research on the horizon.

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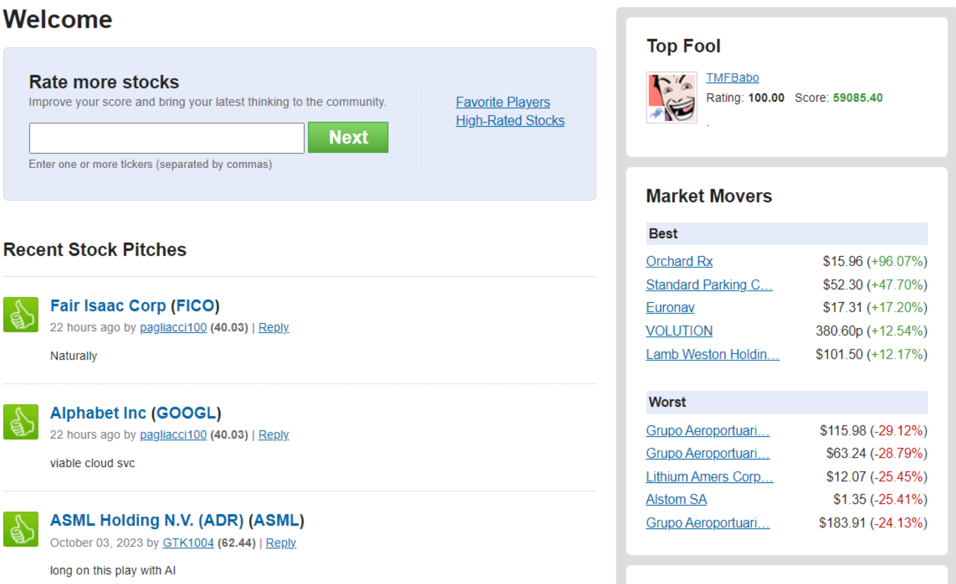
Figure 1: Example of CAPS User Homepage and Stock Prediction Page. This figure presents the screenshot of a CAPS user homepage in Panel A, inviting the user to make a prediction about a stock. Panel B shows the stock prediction page after the user has entered a stock ticker and clicked the "Next" button shown in Panel A.

A: User Homepage



B: Stock Prediction Page

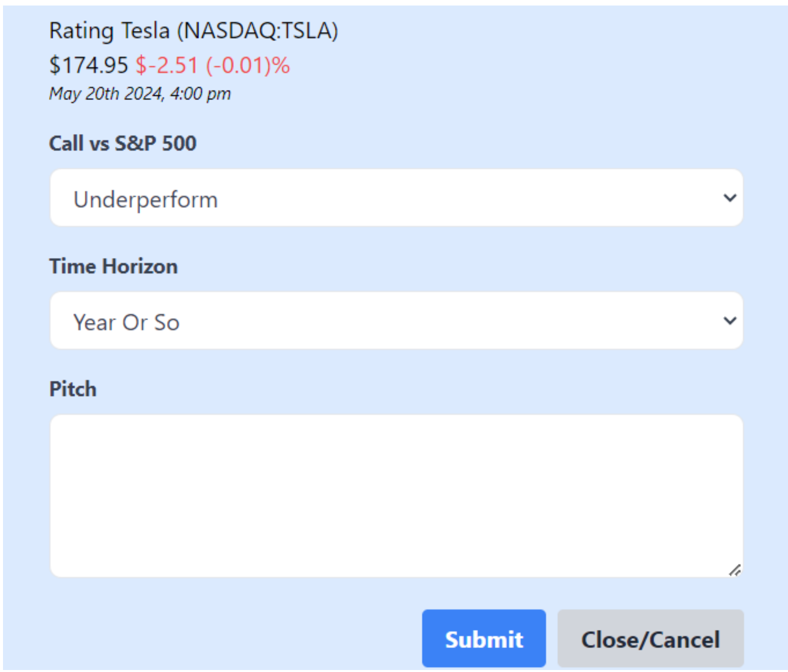


Figure 2: Example of CAPS Pitches. This figure shows sample pitches accompanying predictions that a stock will outperform or underperform the market index for different expectation horizons.

A: Three-week Outperform Pitch

Cisco Sys Inc (CSCO)

aisaak (< 20) Submitted: 2/07/07 8:41 PM :

Start Price: **$19.21**
CSCO Score: **-32.67**

Technical Analysis of the stock- similar linear regression for a one month period will yield a 5% gain within a month or so.
Understanding of the underlying technology:
Cisco owns the base of the internet which will continue to boom for at least 10 years.

Replies: 0 | Reply | Permalink   Report this Post

B: Three-week Underperform Pitch

3m Co (MMM)

KJLKurt (< 20) Submitted: 4/25/08 5:19 PM :

Start Price: **$48.68**
MMM Score: **133.75**

This stock hasn't chose what it wants to do. Its been staying pretty steady (within $10) just when you think its on the up run, it goes back down, and just when you think it might keep going down it starts to go back up. this stock is defiantly one to keep an eye on. once this stock breaks its trend its going to go far, whether thats up or down. Knowing 3m the stock shouldn't go down too much. Ultimately i think this stock is always a good long term stock. but talking short term, it would be a good idea to make some money off this by selling calls or puts or any strategy that will make you money while the stock stays pretty steady.

Replies: 0 | Reply | Permalink   Report this Post

C: One-year Outperform Pitch

Apple, Inc. (AAPL)

MemphisGolfpro (< 20) Submitted: 9/10/15 3:43 PM :

Start Price: **$25.40**
AAPL Score: **468.01**

The next 12 months will be staggering results on pipeline of releases from devices to an incredible advance in eco and enterprise...
Self financing for products will help to get newbies into the appl world
announced unlocked to all carriers
China still a moderate concern however, who knows what lies have been told by pboc and Gov

Replies: 0 | Reply | Permalink   Report this Post

D: One-year Underperform Pitch

Royal Caribbean Cruises Ltd. (RCL)

advsys (< 20) Submitted: 10/03/06 7:52 PM :

Start Price: **$32.21**
RCL Score: **59.42**

This is pure consumer discretionary. As the housing and economy slow over the next 6 months this company will see a serious decline in bookings

Replies: 0 | Reply | Permalink   Report this Post

E: Five-year Outperform Pitch

GameStop Corp. (GME)

mgiamalis (< 20) Submitted: 8/15/09 4:00 PM :

Start Price: **$4.40**
GME Score: **-98.23**

Gamestop is a great company, and this is a great time to buy in. GME is one of the fastest growing video game retailers around, with more and more new locations from mall to mall across America. With tremendous revenue and earnings growth the company looks great going into the future. The retailer holds a wider variety of games and accessories than one of its main competitors, Wal Mart, and it has great growth potential for the future. It has a low PEG ratio of .6. It has a P/E ratio of 10.8, (50% of its 5y average P/E.) The stock is selling for $25, and last year with lower revenue streams and EPS, it was selling for over $50!

Replies: 0 | Reply | Permalink   Report this Post

F: Five-year Underperform Pitch

Best Buy Co., Inc. (BBY)

acadaburn (< 20) Submitted: 9/20/11 1:36 AM :

Start Price: **$17.15**
BBY Score: **-43.05**

Customer service has been lacking lately customers are finally catching on ... Cheaper alternatives on the web and it makes a big difference expecaly when the staff at best buy is now Worse than ever

and there return policy and warrentie policy's have been leaving a bad taste in customer mouths best buy will die within 5 to 10 years if they do not change soon

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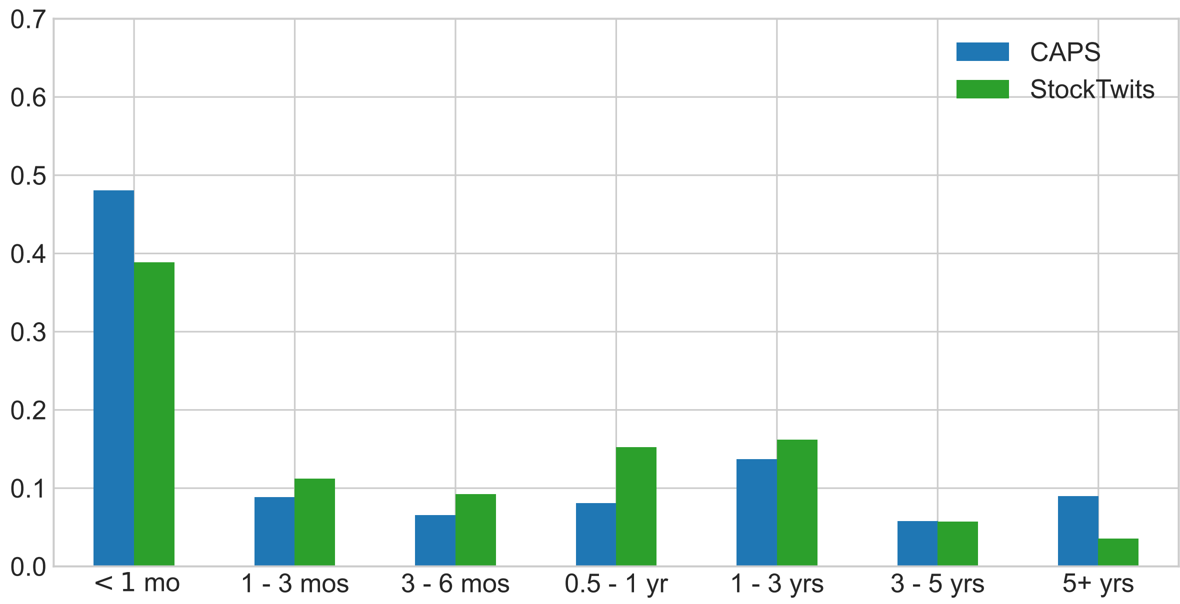
Figure 3: Distribution of User Age, Investment Experience and Risk Tolerance. Panel A plots the fraction of users (y-axis) that lasted n-years (x-axis) on CAPS and StockTwits, respectively. The sample consists of users with at least two predictions, and each user's duration on each platform is calculated as the number of years between their first and last posts. Panel B plots the fraction of users (y-axis) that declare a given level of investment experience and risk tolerance (x-axis) on their CAPS user profile relative to the number of users that declare either characteristic.

A: Share of CAPS and StockTwits Users by Platform Age Bins



B: Share of CAPS Users by Declared Experience and Risk Tolerance Levels

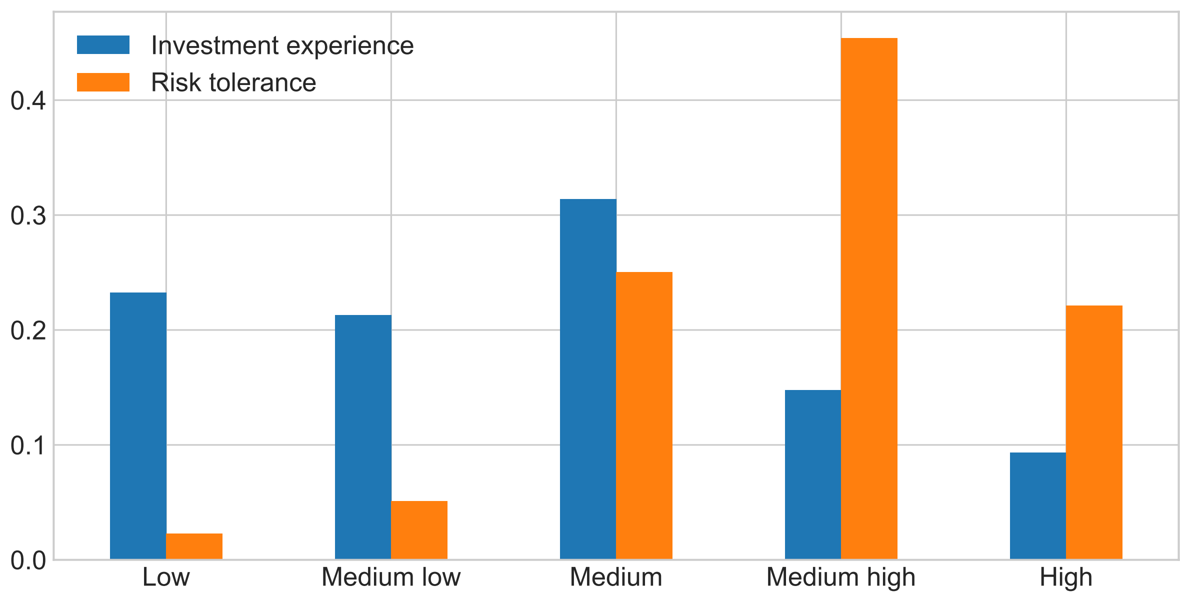
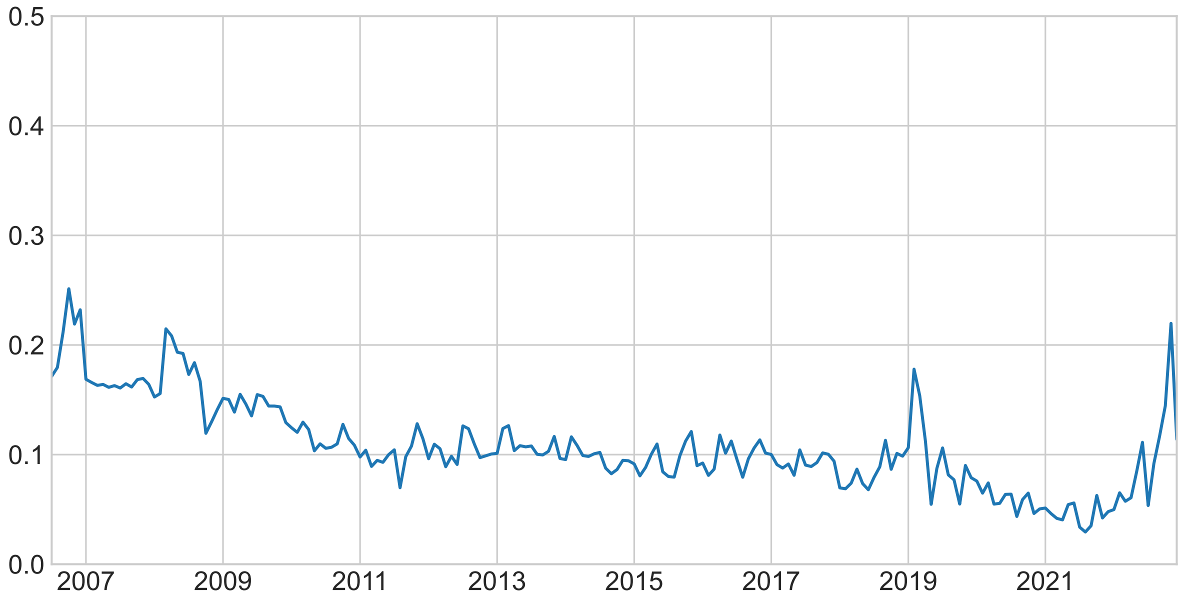


Figure 4: Evolution of Relative Activity and Sentiment Gap across Horizons. Panel A plots the fraction of the total predictions on CAPS per month that choose a short horizon. Panel B plots the difference between the monthly average sentiment of long-horizon predictions and that of short-horizon predictions, i.e., the sentiment gap. The dashed black line shows the 12-month moving average of the monthly sentiment gap. Short horizon refers to the three-week and three-month horizons, and long horizon refers to all other horizons, including unspecified.

A: Share of Short Horizon Predictions



B: Ave. Long Horizon Sentiment minus Ave. Short Horizon Sentiment

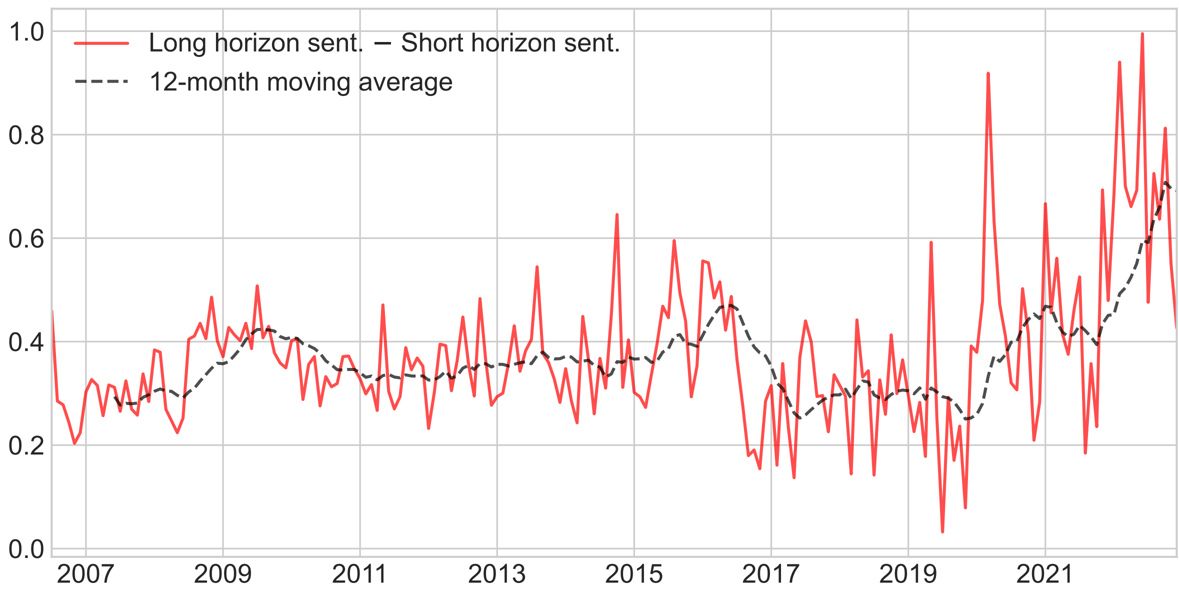


Figure 5: Most Frequent Terms in Pitches by Horizon. The figure shows the relative frequency of the top 10 most occurring bigrams in the pitches that accompany predictions for different horizons. To obtain the relative frequencies plotted in each panel, we divide the frequency of each term by the total frequency of the top 10 terms for that horizon.

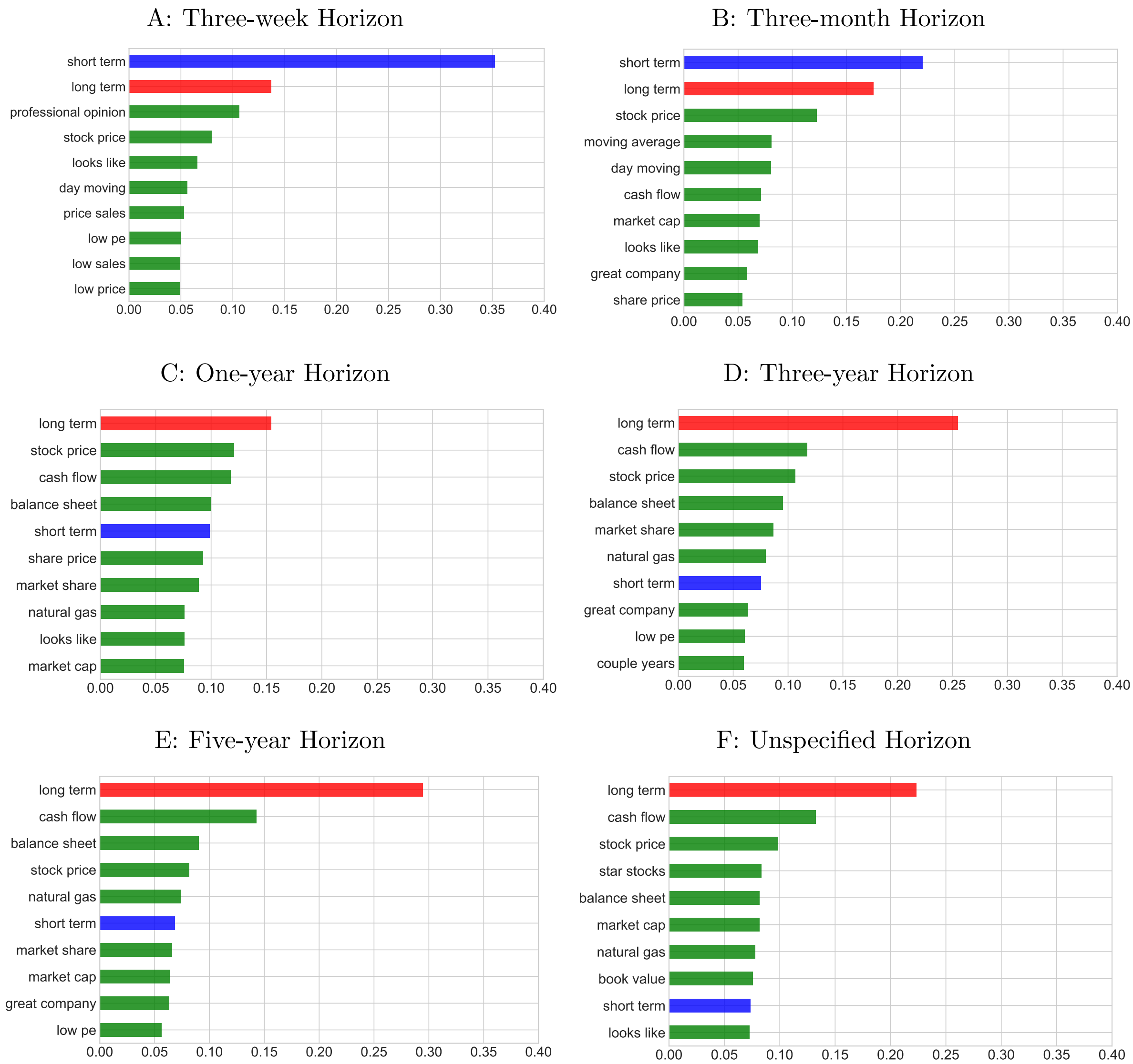


Figure 6: Average Pitch Loadings on Long-term and Short-term Topics by Horizon. The figure shows the average loading of the pitches for different horizons on dictionaries for the long-term vs. short-term topic (Panel A) and the average for the difference in loadings on the long-term and short-term topics (Panel B). The loadings are multiplied by 100 to facilitate exposition.

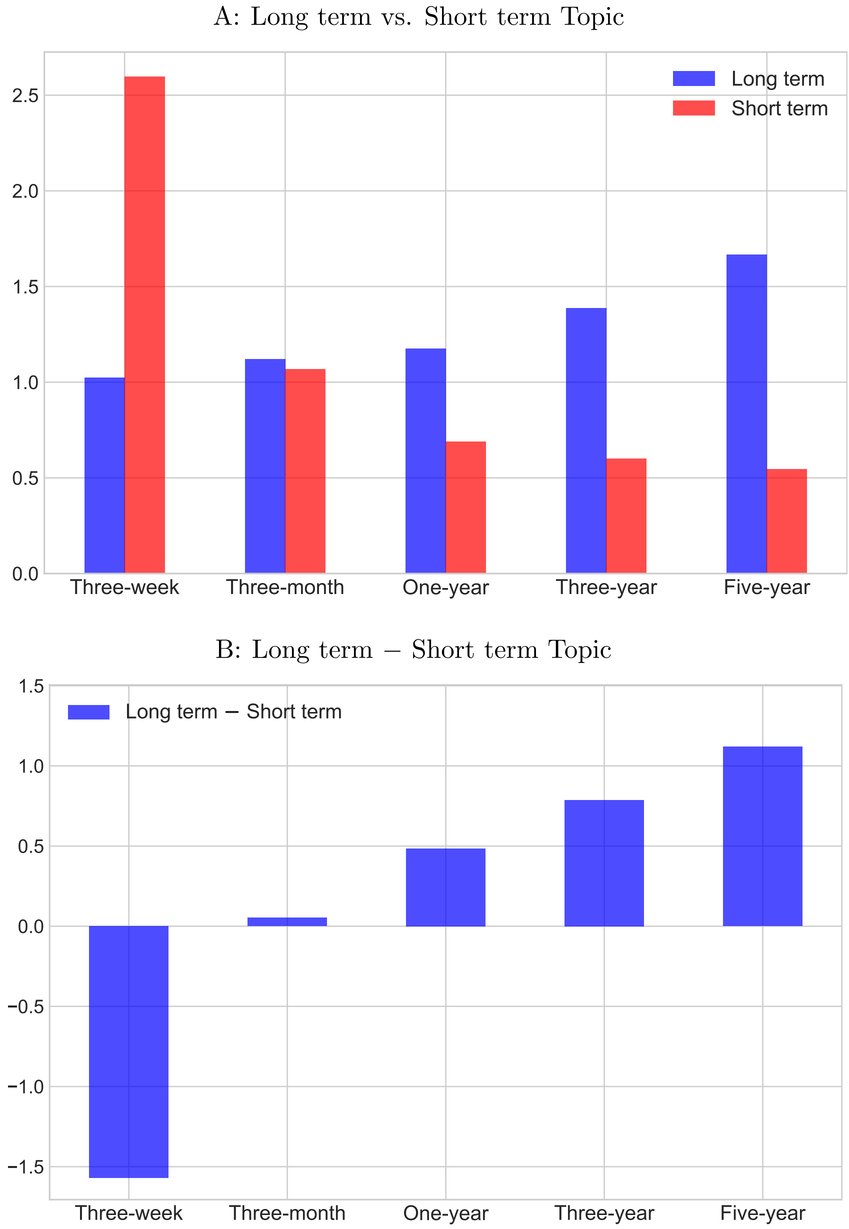


Figure 7: Average Pitch Loadings on Fundamental and Technical Topics by Horizon. The figure shows the average loading of the pitches for different horizons on dictionaries for the fundamental vs. technical topic (Panel A) and the average for the difference in loadings on the fundamental and technical topics (Panel B). The loadings are multiplied by 100 to facilitate exposition.

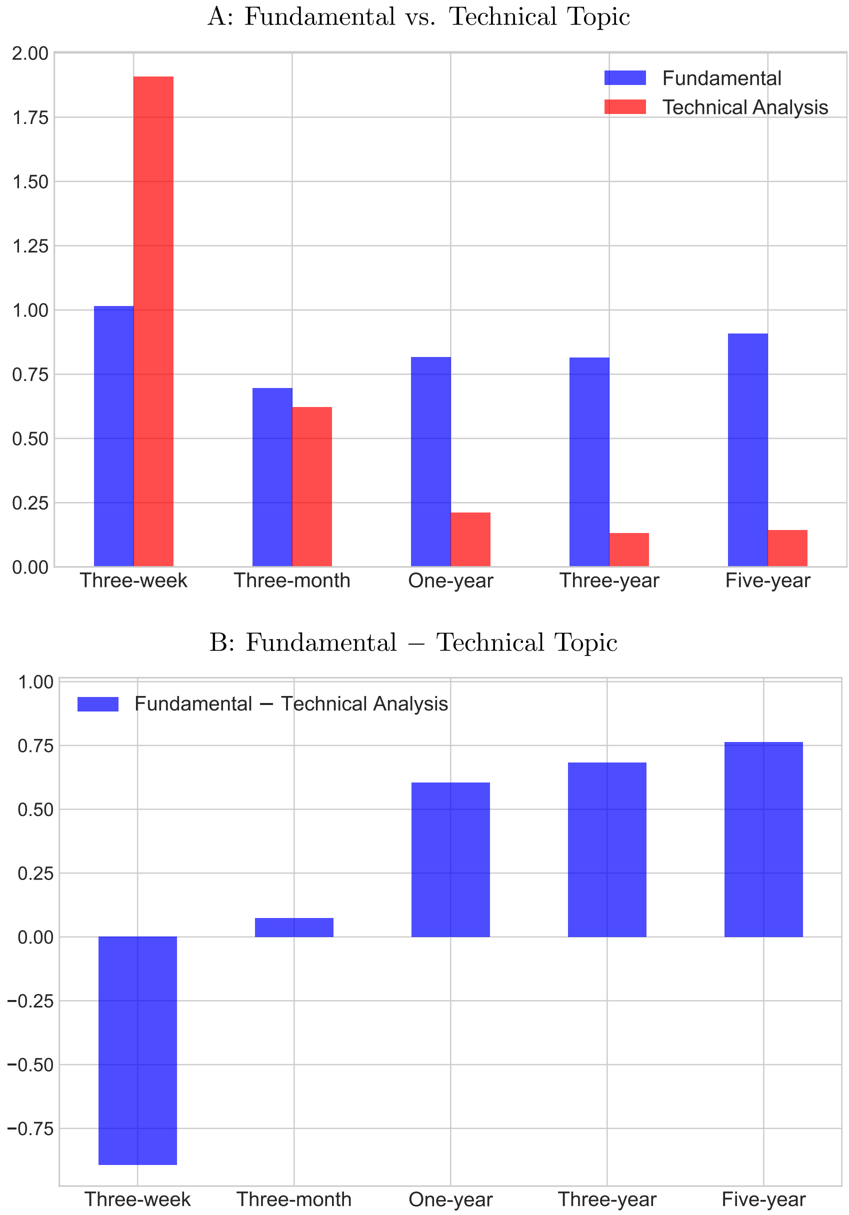
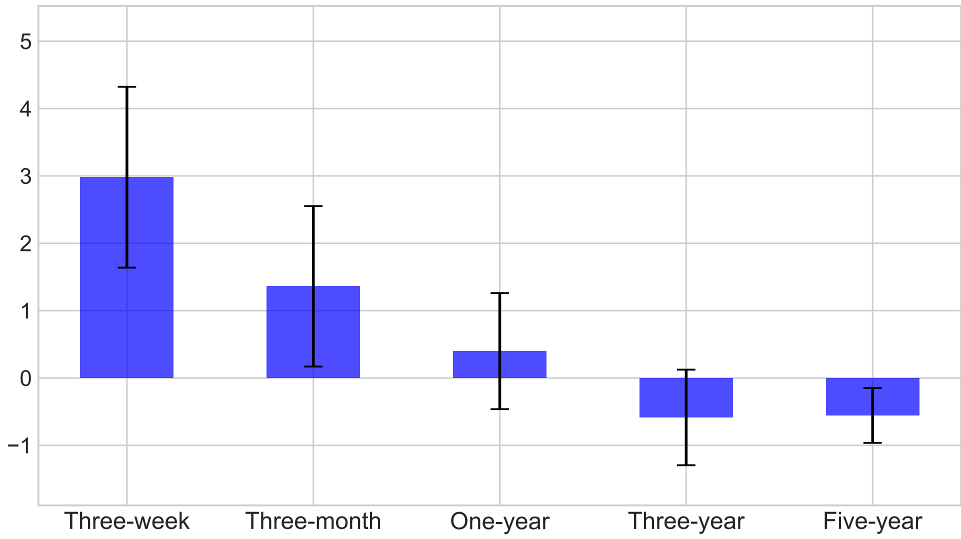


Figure 8: Horizon Belief Response to Earnings Announcements. The figure summarizes the coefficient estimates and 90% confidence intervals from regressing the sentiment of user i's forecast about stock k on day t for horizon h (denoted on the x-axis) on dummy variables for positive earnings announcement day (Panel A) and negative earnings announcement day (Panel B) using the following specification:

$$Outperform_{i(k,t)}(h) = b_1 Positive\ EA_{k,t} + b_2 Negative\ EA_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before and one week after the positive and negative earnings announcements, respectively, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-25$ to $t-6$), and Volatility ($t-5$ to $t-1$). In each panel, the bar corresponding to a given horizon h is obtained from a panel data regression using only predictions for that horizon. Standard errors are double clustered by stock and day.

A: Positive Earnings Announcement



B: Negative Earnings Announcement

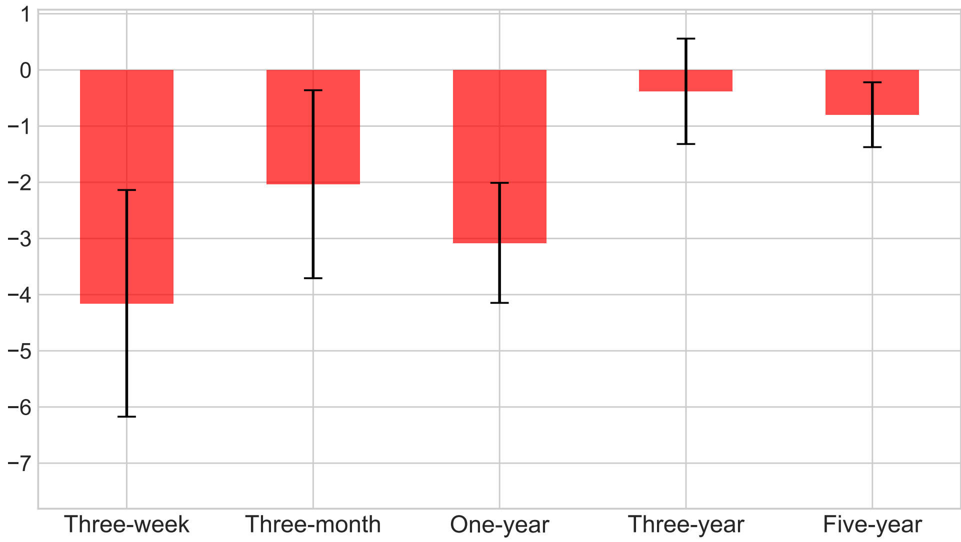
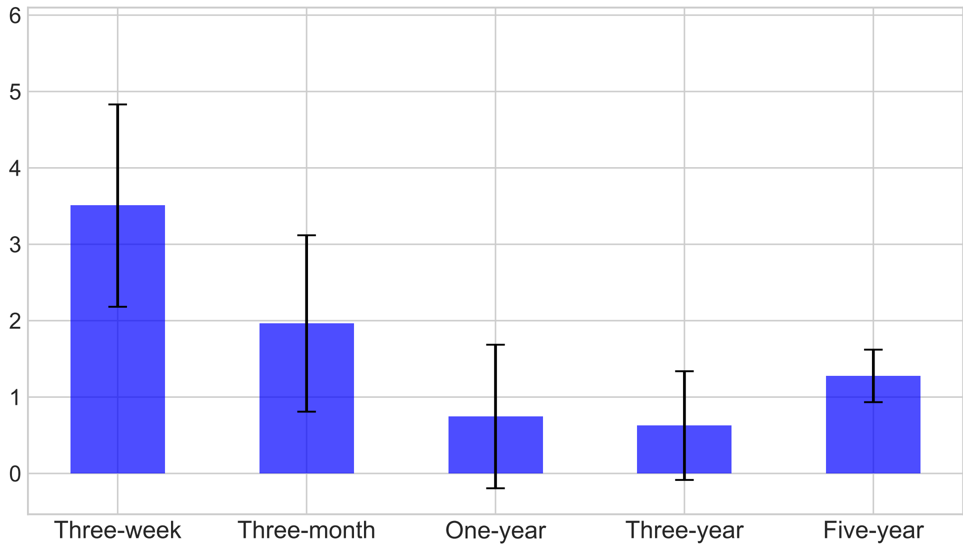


Figure 9: Horizon Belief Response to Technical View Coverage in the News. The figure summarizes the coefficient estimates and 90% confidence intervals from regressing the sentiment of user i's forecast about stock k on day t for horizon h (denoted on the x-axis) on dummy variables for technical view announcement day and one-week after technical view announcement, using the following specification:

$$Outperform_{i(k,t)}(h) = b_1\, Technical\ View\ Ann_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before and one week after the announcement, respectively, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-25$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regressions are estimated separately for bullish (Panel A) and bearish (Panel B) technical views. In each panel, the bar corresponding to a given horizon h is obtained from a panel data regression using only predictions for that horizon. Standard errors are double clustered by stock and day.

A: Bullish Technical View



B: Bearish Technical View

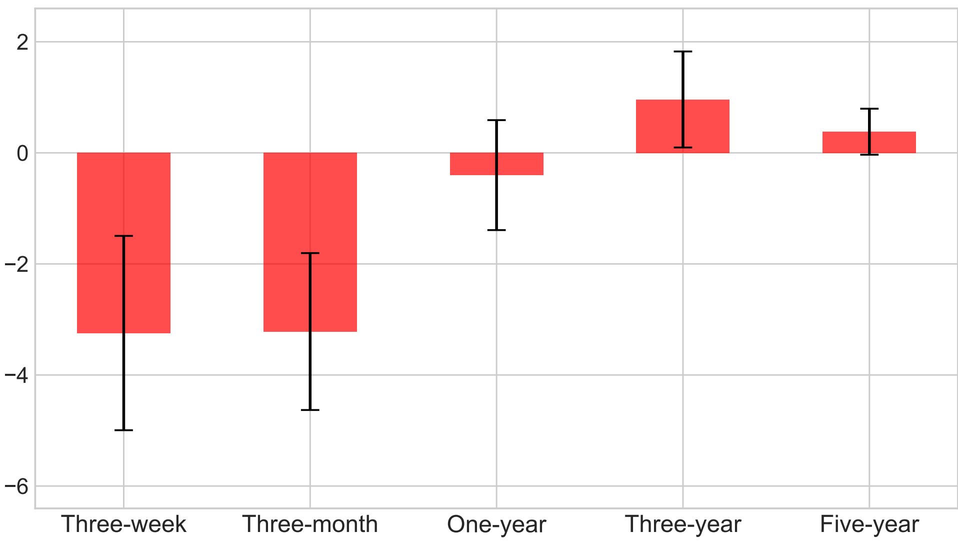


Figure 10: Horizon Belief Response to Target Rumors. The figure summarizes the coefficient estimates and 90% confidence intervals from regressing the sentiment of user i's forecast about stock k on day t for horizon h (denoted on the x-axis) on dummy variables for the announcement day in the media and one week after the announcement of rumors about firm k being the target of an acquisition, using the following specification:

$$Outperform_{i(k,t)}(h) = b_1 \, Target\ Rumor_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before and one week after the announcement, respectively, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-25$ to $t-6$), and Volatility ($t-5$ to $t-1$). In each panel, the bar corresponding to a given horizon h is obtained from a panel data regression using only predictions for that horizon. Standard errors are double clustered by stock and day.

A: Target Rumor

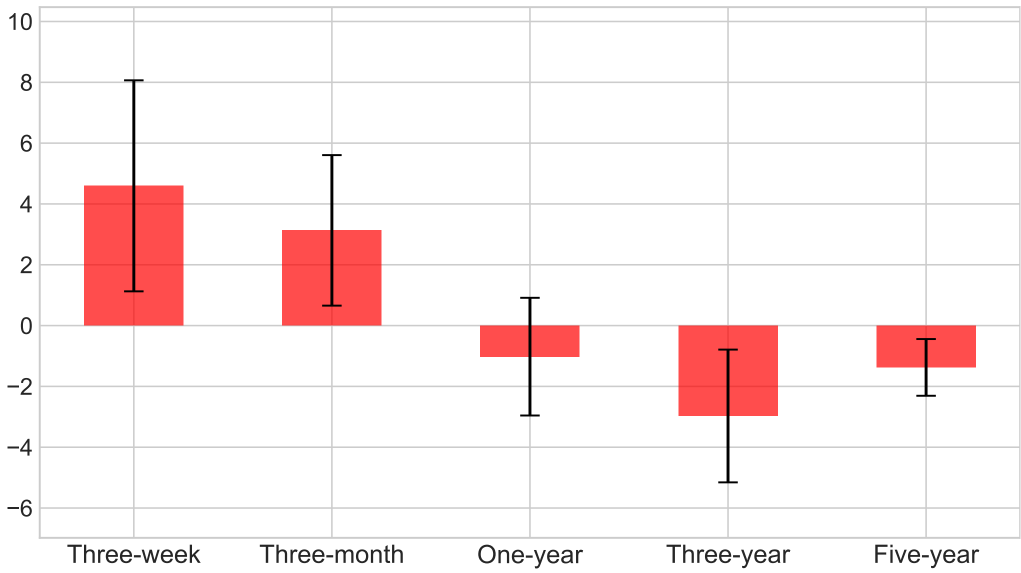


Figure 11: Trading Volume and Horizon Disagreement around Events. The figure summarizes the coefficient estimates and 90% confidence intervals of the *Horizon Disagreement* and *Horizon Disagreement* + *Horizon Disagreement* × *Ann.* terms from panel regressions of abnormal log volume on the Horizon disagreement and its interaction with an event's announcement day dummy, denoted Ann. The regressions are estimated separately for each event (earnings announcements, technical views, and target rumors) denoted on the x-axis. The plotted values are based on the estimates reported in columns (1), (3) and (5) of Table 8, which reports the full estimates for these events. The regressions include the controls described in the aforementioned table and stock and day fixed effects. The standard errors are double clustered by stock and day.

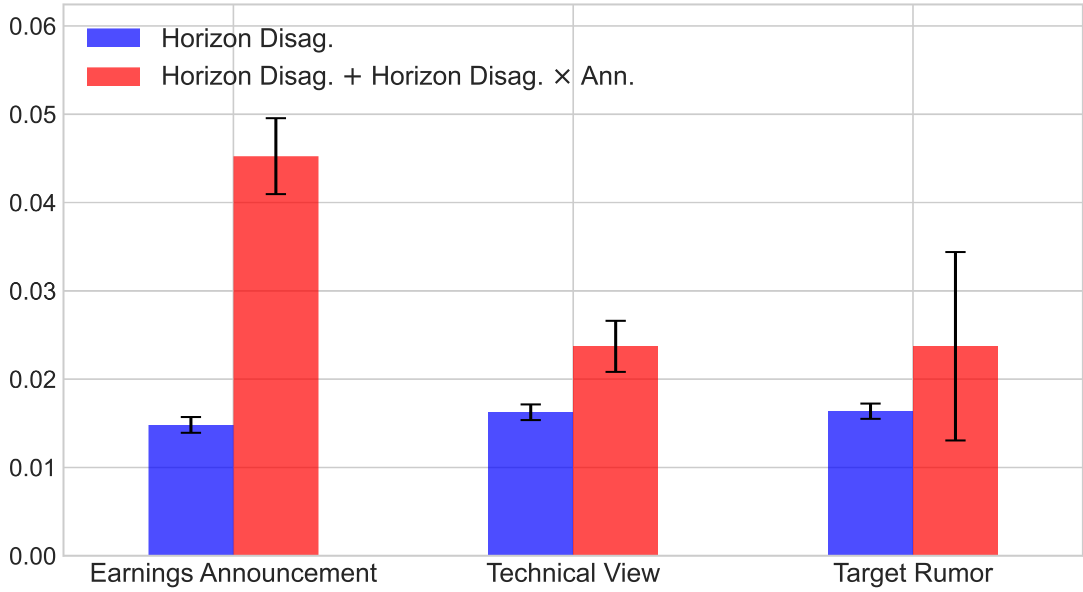


Table 1: Summary CAPS Data. This table reports summary statistics of the CAPS data. Panel A summarizes the frequency and sentiment of predictions across the expectation horizons. "# pitches" refers to the number of predictions that contain a pitch for the specified horizon. "# unique users" refers to the number of unique forecasters that made at least one prediction over a specified horizon. Similarly, "# unique stocks" refers to the number of unique stocks that received at least one prediction for the specified horizon. To quantify user sentiment, we assign a value of 1 (-1) to predictions that a stock will outperform (underperform) the market. Panel B summarizes the activity on CAPS. Panel C summarizes the sentiment of predictions across all predictions, per user and per stock. Panel D summarizes the characteristics of the pitches that accompany the predictions. Panel E summarizes the characteristics of the stocks that received predictions on CAPS. Summary of the stock characteristics is obtained from the cross-section of the average values of the characteristics for each stock as of the prediction day.

Panel A: Summary of Prediction Horizons					
	# predictions	# pitches	# unique users	# unique stocks	Average sentiment
Total	3,115,187	420,287			
Three-week	163,228	21,250	26,655	1,333	0.300
Three-month	270,461	44,732	52,651	1,333	0.442
One-year	457,311	84,451	75,308	1,333	0.613
Three-year	344,684	69,940	63,903	1,333	0.819
Five-year	1,427,871	167,927	77,402	1,333	0.749
Unspecified	451,632	31,987	35,039	1,333	0.672

Panel B: Summary of Activity					
	Mean	SD	10%	50%	90%
# predictions per user	22.615	95.695	2	6	43
# unique stocks per user	18.143	43.201	2	6	40
# unique horizons per user	2.403	1.344	1	2	4
# predictions per stock	2336.974	2998.534	840	1396	4345

Panel C: Summary of Sentiment					
	Mean	SD	10%	50%	90%
All	0.676	0.737	-1.000	1.000	1.000
Per user	0.802	0.370	0.333	1.000	1.000
Per stock	0.661	0.312	0.195	0.783	0.897

Panel D: Summary of Pitches					
	Mean	SD	10%	50%	90%
# characters	168	329	14	81	365
# words	30	57	2	14	66
Polarity	0.252	0.436	-0.307	0.226	0.844

Panel E: Summary of Stock Characteristics					
	Mean	SD	10%	50%	90%
Market Cap. (millions)	13,077	33,120	320	2,697	31,290
Price	45.787	70.43	7.404	30.295	86.805
Book-to-Market	0.512	0.543	0.121	0.417	1.015
Market Beta	1.25	0.386	0.767	1.241	1.74
Idio. Skewness	0.308	0.587	-0.315	0.271	0.96
Idio. Volatility	0.028	0.014	0.014	0.026	0.043

Table 2: Dictionaries for the Topic Categories. This table lists the words that belong to the dictionaries for the short-term, long-term, fundamental and technical analysis topics, respectively. To construct the dictionary, we fit *word2vec* embedding on our pitch corpus and then for each topic category, we find the top 100 words with the largest similarity with the average vector of its seed words. For example, for the "long term" topic, we use "long term, "longrun," and "long haul" as the seed words. For the "short term" topic, we use "short term", "near term", "shortrun", "temporary", and "few month" as the seed words. Appendix C provides further details of the dictionary construction.

Topic	Dictionary
Short term	short_term, complete_rise, near_term, shortrun, temporary, few_month, anticipation_of_the_eventual, pullback_likely, deteriorate_professional, weakening_earnings, few_week, trading_in_mind, macd_and_directional, tort_screen, slight, bounce, shot_gun, my_taget, rsi_stochastic, rebound, pick_ability, group_rotation, entry_point, position_for_approximately, repricing_of_credit, pullback, stockpicking_contest, profit_taking, allstar_back, upward, sure_on_the_timing, game_playing, trade_at_13, tjc, ema_cross, retracement, overshoot, 115_day, public_sentiment, recent, technical_bounce, near_future, sector_rotation, mechanical_investing, bkx_index, options_predictor, expect, 15_day, buying_opportunity, price, favorable_chart, next_serveral, fundamental, consensus_opinion, unfavorable_valuation, weak_and_deteriorating, bit, improve_professional, overreaction, next_6, several_month, timely_industries, mid, resistance_level, dip, 6_month, overestimated_earnings
Long term	long_term, long_haul, longrun, lt, go_forward, future, 4_year, over_the_next, down_the_road, slow_and_steady, decent_dividend, turbulent, next_few, longer, core_holding, 5_year, patient_investor, increasingly_excessive, oversell, dividend_to_boot, divy, long, bumpy, sure, 10_year, good, dividen, volatile, divs, healthy_dividend, next_couple, factset_article, faint_of_heart, roe_and_roa, next_decade, patience, safe_bet, bumpy_ride, steady, ultimately, fundamentally, solid, place_to_park, great, strangle, hold_forever, fundamental_and_momentum, automate_valuation, forseeable_future, eventually, region_of_production, few_year, next_5, account_track, next_several, appropriate_advice, nice, intend_to_test
Fundamental	balance_sheet, cash_flow, roe_and_roa, current_ratio, debt, roe_roa, lever_free, roe, return_on_equity, income_statement, free_cash, roa_roe, cashflow, fcf, equity_ratio, piotroski_screen, cash_on_hand, roa_and_roe, quick_ratio, p_b, weak_and_deteriorating, fundamental, return_on_asset, no_debt, capital_structure, profit_margin, lt_debt, management_effectiveness, roa, roic, interest_coverage, liabilities, cash, spreadsheet_devle, consensus_opinion, ebit_ev, ratio, return_on_assets, generic_free, debt_equity, manageable_debt, insider_ownership, net_profit, ocf, book_value, zero_debt, total_liability, strong_balance, earnings_surprise, p_e, margin, operate_margin, ebitd, increasingly_excessive, net_income, factset_article, plenty_of_cash, traile_pe, flow, invest_capital, pristine_balance, payout_ratio, p_fcf, financial_strength, tangible_book, sheet, earning, ev_ebitda, peg, current_metric, peg_ratio, p_bv, q_q, inventory_turnover, clean_balance, interest_expense, roc, eps_growth, insider_institutional, altman_z, wacc, growth_rate, pretax_profit, asset_turnover, dividend, gross_margins, ey, debt_load, ebitda
Technical analysis	macd_and_directional, oscillator, rsi_stochastic, ema_cross, moving_average, move_average, rsi, 115_day, my_target, macd, 200_day, tort_screen, 50_day, above_the_200, bollinger, stochastic, weekly_chart, volatility_beta, stochastics, day_move, sma, trendspotter, technical_analysis, 40_day, stoch, complete_rise, candlestick, nerosagetrade, unfavorable_valuation, resistance_level, grp_rs, pullback_likely, ema, 20_day, trend_spotter, 100_day, overbought, favorable_chart, technical_indicator, indicators, deteriorate_professional, resistance, trendline, cup_with_handle, professional_opinion, sales_and_return, divergence, technical, trading_in_mind, momentum, chart_pattern, likely_on_volatile, chart, capitalization_great, options_predictor, cup_and_handle, dma, signals, below_normal, toppy, uptrend, bkx_index, pull_back, shot_gun, rs_rating, retracement, pick_ability, allstar_back, group_rotation, breakout, technically, barchart_com, wedge, starsopen, industries_and_sectors, retrace, revise_upward, parabolic, stockpicking_contest, tjc, portfolio_of_smallish, triangle, technical_bounce, relative_strength, uptrende, head_and_shoulder, improve_professional, krx

Table 3: Pitch Loading on Long-term vs. Short-term Topics across Forecast Horizons. The table shows the results of regressing prediction pitches' loading on a specific topic dictionary on indicator variables for the prediction horizons as follows:

$$Topic\ Loading_{i(k,t)} = \alpha_i + \nu_k + \gamma_t + \sum_{h \in H} b_h \times \mathbb{1}_{horizon_{i(k,t)}} + \epsilon_{i,k,t}$$

$Topic\ Loading_{i(k,t)}$ denotes the loading of individual i's pitch accompanying the forecast about stock k on day t on a specific topic category. It captures the difference between the long-term and short-term dictionary loadings (Long term − Short term). $Topic\ Loading_{i(k,t)}$ is normalized to unit variance to facilitate comparison. $\mathbb{1}_{horizon_{i(k,t)}}$ is an indicator variable for the different horizons $horizon \in \{\text{Three-month, One-year, Three-year, Five-year, Unspecified}\}$, where the Three-week horizon serves as the base. The sample includes only predictions with pitches. Standard errors, in parentheses, are double clustered by stock and day.

	Long term − Short term			
	(1)	(2)	(3)	(4)
Constant	-0.283**			
	(0.132)			
Three-month	0.292**	0.117***	0.117***	0.114***
	(0.132)	(0.020)	(0.019)	(0.019)
One-year	0.370***	0.193***	0.193***	0.185***
	(0.132)	(0.021)	(0.020)	(0.020)
Three-year	0.424***	0.256***	0.255***	0.244***
	(0.132)	(0.023)	(0.021)	(0.021)
Five-year	0.484***	0.318***	0.320***	0.298***
	(0.133)	(0.022)	(0.020)	(0.020)
Unspecified	0.418***	0.234***	0.231***	0.219***
	(0.133)	(0.024)	(0.023)	(0.022)
User FE	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes
Stock FE	No	No	No	Yes
R-squared Adj.	0.012	0.167	0.171	0.175
Obs.	419,579	419,579	419,579	419,579

Table 4: Pitch Loading on Fundamental vs. Technical Topics across Forecast Horizons. The table shows the results of regressing prediction pitches' loading on a specific topic dictionary on indicator variables for the prediction horizons as follows:

$$Topic\ Loading_{i(k,t)} = \alpha_i + \nu_k + \gamma_t + \sum_{h \in H} b_h \times \mathbb{1}_{horizon_{i(k,t)}} + \epsilon_{i,k,t}$$

$Topic\ Loading_{i(k,t)}$ denotes the loading of individual i's pitch accompanying the forecast about stock k on day t on a specific topic category. It captures the difference between the fundamental and technical analysis dictionary loadings (Fundamental − Technical Analysis). $Topic\ Loading_{i(k,t)}$ is normalized to unit variance to facilitate comparison. $\mathbb{1}_{horizon_{i(k,t)}}$ is an indicator variable for the different horizons $horizon \in \{\text{Three-month}, \text{One-year}, \text{Three-year}, \text{Five-year}, \text{Unspecified}\}$, where the Three-week horizon serves as the base. The sample includes only predictions with pitches. Standard errors, in parentheses, are double clustered by stock and day.

	Fundamental − Technical Analysis			
	(1)	(2)	(3)	(4)
Constant	-0.196***			
	(0.068)			
Three-month	0.213***	0.128***	0.127***	0.123***
	(0.071)	(0.019)	(0.019)	(0.019)
One-year	0.330***	0.204***	0.202***	0.195***
	(0.069)	(0.019)	(0.018)	(0.018)
Three-year	0.347***	0.217***	0.213***	0.205***
	(0.070)	(0.019)	(0.019)	(0.018)
Five-year	0.364***	0.227***	0.227***	0.218***
	(0.068)	(0.020)	(0.019)	(0.019)
Unspecified	0.283***	0.181***	0.176***	0.168***
	(0.069)	(0.019)	(0.019)	(0.019)
User FE	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes
Stock FE	No	No	No	Yes
R-squared Adj.	0.007	0.150	0.163	0.169
Obs.	419,579	419,579	419,579	419,579

Table 5: Belief by Horizon around Earnings Announcement. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h, i.e., $\textit{Outperform}_{i,k,t}(h)$, on a dummy variable for positive and negative earnings announcements (EA), respectively, using the following specification:

$$\textit{Outperform}_{i(k,t)}(h) = b_1 \textit{Positive EA}_{k,t} + b_2 \textit{Negative EA}_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$\textit{Outperform}_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Standard errors, reported in parentheses, are double clustered by stock and day.

	Sentiment (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Positive EA	2.980***	1.361*	0.399	-0.585	-0.556**
	(0.816)	(0.724)	(0.524)	(0.431)	(0.248)
Negative EA	-4.155***	-2.034**	-3.078***	-0.381	-0.797**
	(1.227)	(1.017)	(0.650)	(0.570)	(0.351)
Controls	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
% Outperform Predictions	64.96	72.17	80.77	91.01	87.64

Table 6: Summary of Disagreement Measures. This table reports summary statistics for the disagreement measures. Panel A shows the mean and standard deviation of the CAPS Disagreement, i.e., disagreement irrespective of horizon calculated on a given day as the standard deviation of sentiment, and the Horizon Disagreement measure defined in Eq. (4). Panel B shows the correlation of these disagreement measures with StockTwits (ST) investment philosophy-based disagreement measures. Panel C shows the coefficient estimates from regressing the CAPS horizon-based disagreement measures on the ST investment philosophy-based disagreement measures. To facilitate comparison, the right-hand side variables used in the regressions for Panel C are standardized to zero mean and unit variance, while the left-hand side is normalized to unit variance. Standard errors, in parentheses, are double clustered by stock and day. The disagreement measures prefixed by ST in the table are based on StockTwits' investment philosophies.

Panel A: Disagreement Measures

	CAPS Disagreement	Horizon Disagreement	Three-week	Three-month	One-year	Three-year	Five-year
Mean	0.0298	0.0215	0.0015	0.0029	0.0043	0.0017	0.0109
SD	0.1624	0.1377	0.0384	0.0524	0.0639	0.0396	0.1005

Panel B: Correlation of Horizon Disagreement with Philosophy-based Disagreement

	CAPS Disagreement	Horizon Disagreement
ST Disagreement	0.1313	0.1019
ST Within-group Disagreement	0.1799	0.1385
ST Cross-group Disagreement	0.0275	0.0213

Panel C: Regression of Horizon-based Disagreement on Philosophy-based Disagreement

	CAPS Disagreement		Horizon Disagreement	
ST Disagreement	0.131***		0.102***	
	(0.014)		(0.010)	
ST Within-group Disagreement		0.179***		0.138***
		(0.019)		(0.014)
ST Cross-group Disagreement		0.019***		0.015***
		(0.003)		(0.002)
Constant	0.176***	0.176***	0.139***	0.139***
	(0.010)	(0.009)	(0.008)	(0.007)
R-squared Adj.	0.017	0.033	0.010	0.019
Obs.	1,455,054	1,455,054	1,455,054	1,455,054

Table 7: Horizon Disagreement and Trading Volume. This table reports the results of the panel regression of abnormal log volume on the horizon-based disagreement measure and several controls. In some specifications, we control for the StockTwits philosophy-based disagreement measures (prefixed by ST). Each disagreement measure is standardized to zero mean and unit variance to facilitate comparison. All specifications include stock and day fixed effects. Standard errors, in parentheses, are double clustered by stock and day.

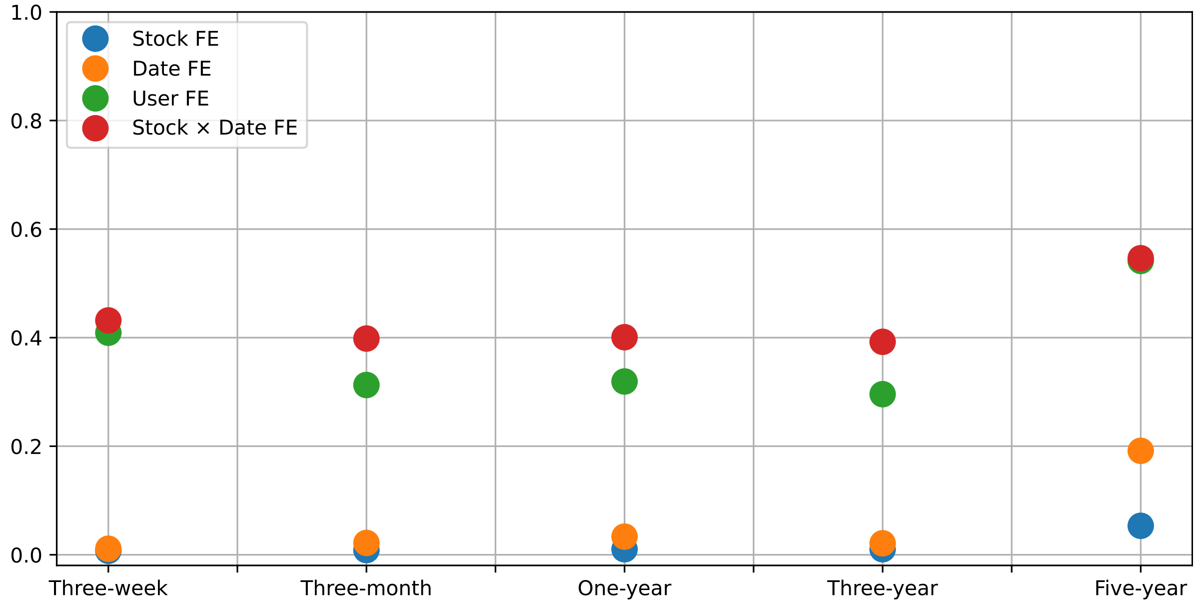
	Abnormal Log Volume (t)				
	(1)	(2)	(3)	(4)	(5)
Horizon Disagreement (t)	0.016***			0.014***	
	(0.001)			(0.001)	
ST Disagreement (t)		0.086***			
		(0.002)			
ST Within-group Disagreement (t)			0.115***	0.114***	
			(0.003)	(0.003)	
ST Cross-group Disagreement (t)			0.039***	0.039***	
			(0.001)	(0.001)	
Horizon Disagreement (t-1)					0.005***
					(0.000)
Abn. Log Volume (t-1)	0.558***	0.582***	0.574***	0.573***	0.559***
	(0.009)	(0.003)	(0.003)	(0.003)	(0.009)
Abn. Ret (t-25 to t-6)	0.031***	0.012	0.010	0.011	0.030***
	(0.006)	(0.009)	(0.009)	(0.009)	(0.006)
Abn. Ret (t-5 to t-1)	-0.037***	-0.016	-0.011	-0.009	-0.039***
	(0.008)	(0.012)	(0.013)	(0.013)	(0.008)
Volatility (t-5 to t-1)	0.321***	-0.398***	-0.602***	-0.617***	0.341***
	(0.077)	(0.046)	(0.051)	(0.052)	(0.078)
News Media (t)	0.108***	0.098***	0.087***	0.086***	0.109***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared Adj.	0.477	0.517	0.528	0.528	0.477
Obs.	4,339,738	1,455,007	1,455,007	1,455,007	4,339,738

Table 8: Disagreement and Trading Volume around Events. This table reports the results of the panel regression of abnormal log volume on the horizon-based disagreement measures interacted with dummy variables for days around specific event announcements. The column header denotes the event type, while "Ann." denotes the announcement day dummy variable. "1 wk before Ann." denotes the dummy variable for one week before an announcement. "1 wk after Ann." denotes the dummy variable for one week after an announcement. The specification includes the interactions of disagreement measures with the "1 wk before Ann." and "1 wk after Ann." dummies, but their coefficients are suppressed for brevity. The disagreement measures are standardized to zero mean and unit variance to facilitate comparison. All specifications include stock and day fixed effects. Standard errors, in parentheses, are double clustered by stock and day.

	Abnormal Log Volume					
	Earnings Announcement		Technical View		Target Rumor	
	(1)	(2)	(5)	(6)	(3)	(4)
Horizon Disagreement × Ann.	0.030***	0.022***	0.007***	-0.010***	0.007	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.006)	(0.006)
Horizon Disagreement	0.015***	0.013***	0.016***	0.017***	0.016***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ST Within-group Disagreement × Ann.		0.014***		0.023***		0.008
		(0.004)		(0.006)		(0.012)
ST Cross-group Disagreement × Ann.		0.030***		0.013***		0.028**
		(0.004)		(0.002)		(0.013)
ST Within-group Disagreement		0.101***		0.112***		0.114***
		(0.003)		(0.004)		(0.003)
ST Cross-group Disagreement		0.035***		0.038***		0.039***
		(0.001)		(0.001)		(0.001)
1 wk before Ann.	0.050***	0.052***	0.007***	0.005	0.041***	0.029***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
Ann.	0.454***	0.318***	0.034***	0.045***	0.242***	0.163***
	(0.008)	(0.009)	(0.002)	(0.004)	(0.014)	(0.014)
1 wk after Ann.	0.086***	0.075***	-0.004**	-0.003	0.015***	-0.001
	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)
Abn. Log Volume (t-1)	0.552***	0.567***	0.558***	0.573***	0.558***	0.573***
	(0.009)	(0.004)	(0.009)	(0.003)	(0.009)	(0.003)
Abn. Ret (t-25 to t-6)	0.032***	0.013	0.031***	0.012	0.031***	0.011
	(0.007)	(0.009)	(0.006)	(0.009)	(0.006)	(0.009)
Abn. Ret (t-5 to t-1)	-0.034***	-0.005	-0.038***	-0.010	-0.038***	-0.010
	(0.008)	(0.012)	(0.008)	(0.013)	(0.008)	(0.013)
Volatility (t-5 to t-1)	0.284***	-0.561***	0.321***	-0.610***	0.316***	-0.618***
	(0.073)	(0.050)	(0.077)	(0.051)	(0.077)	(0.052)
News Media (t)	0.085***	0.066***	0.108***	0.086***	0.108***	0.086***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared Adj.	0.486	0.537	0.478	0.529	0.478	0.529
Obs.	4,339,738	1,455,007	4,343,109	1,456,857	4,339,738	1,455,007

A Additional Figures

Figure A1: Variation in Horizon Choice Explained by Fixed Effects. The figure plots the R^2 from regressing the dummy variable for a given horizon h (the x-axis) on the set of fixed effects indicated in the legend. The dummy variable for each horizon h equals one for predictions whose horizon equals h and zero otherwise.



B Additional Tables

Table A1: Observations across Data Filtering. The table shows the number of observations in the data set as we iteratively apply the filters denoted in the table and described in Section 2.2.

	# Predictions	# Pitches	# Users	# Stocks
Full sample	6,581,687	832,953	199,228	12,434
Merge with CRSP	5,414,184	679,909	189,430	9,489
Keep common stocks (i.e., share code 10/11/12)	4,232,195	555,860	183,494	6,665
Retain individuals with at least 2 predictions	4,187,889	541,809	139,188	6,662
Keep stocks with top 20% of predictions	3,115,187	420,287	137,750	1,333

Table A2: Pitch Loading on Long- vs Short-term Topics across Horizons. The table shows the results of regressing prediction pitches' loading on specific topic dictionaries on indicator variables for the prediction horizons as follows:

$$Loading_{i(k,t)} = a_0 + \sum_{h \in H} b_h \mathbb{1}(h)_{i(k,t)} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Loading_{i(k,t)}$ is a generic label that denotes the loading of individual i's pitch accompanying the forecast about stock k on day t on either the long-term dictionary or short-term dictionary as indicated in the table header. $Loading_{i(k,t)}$ is normalized to unit variance to facilitate comparison. $\mathbb{1}(h)_{i(k,t)}$ is an indicator variable for the different horizons $h \in$ {Three-month, Three-month, One-year, Three-year, Five-year, Unspecified}, where the Three-week horizon serves as the base. The sample includes only predictions with pitches. Standard errors, in parentheses, are double clustered by stock and day.

	Long term				Short term			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.232***				0.761***			
	(0.010)				(0.220)			
Three-month	0.022*	0.002	0.004	0.002	-0.448**	-0.188***	-0.184***	-0.183***
	(0.012)	(0.010)	(0.010)	(0.010)	(0.220)	(0.030)	(0.028)	(0.028)
One-year	0.034***	0.017*	0.019*	0.011	-0.559**	-0.292***	-0.290***	-0.288***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.220)	(0.033)	(0.030)	(0.030)
Three-year	0.082***	0.071***	0.073***	0.057***	-0.585***	-0.325***	-0.322***	-0.323***
	(0.012)	(0.010)	(0.010)	(0.010)	(0.220)	(0.035)	(0.032)	(0.032)
Five-year	0.145***	0.134***	0.138***	0.110***	-0.601***	-0.345***	-0.342***	-0.343***
	(0.023)	(0.012)	(0.012)	(0.011)	(0.220)	(0.032)	(0.030)	(0.029)
Unspecified	0.081***	0.057***	0.053***	0.039**	-0.576***	-0.307***	-0.308***	-0.307***
	(0.022)	(0.018)	(0.017)	(0.017)	(0.220)	(0.033)	(0.030)	(0.030)
User FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	No	No	Yes	Yes
Stock FE	No	No	No	Yes	No	No	No	Yes
R-squared Adj.	0.003	0.177	0.181	0.187	0.018	0.155	0.159	0.161
Obs.	419,579	419,579	419,579	419,579	419,579	419,579	419,579	419,579

Table A3: Pitch Loading on Fundamental vs. Technical Topics across Horizons. The table shows the results of regressing prediction pitches' loading on specific topic dictionaries on indicator variables for the prediction horizons as follows:

$$Loading_{i(k,t)} = a_0 + \sum_{h \in H} b_h \mathbb{1}(h)_{i(k,t)} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Loading_{i(k,t)}$ is a generic label that denotes the loading of individual i's pitch accompanying the forecast about stock k on day t on either the fundamental dictionary or the technical analysis dictionary as indicated in the table header. $Loading_{i(k,t)}$ is normalized to unit variance to facilitate comparison. $\mathbb{1}(h)_{i(k,t)}$ is an indicator variable for the different horizons $h \in$ {Three-month, Three-month, One-year, Three-year, Five-year, Unspecified}, where the Three-week horizon serves as the base. The sample includes only predictions with pitches. Standard errors, in parentheses, are double clustered by stock and day.

	Fundamental				Technical Analysis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.284***				0.691***			
	(0.095)				(0.229)			
Three-month	-0.090	0.044***	0.044***	0.040***	-0.466**	-0.153***	-0.152***	-0.151***
	(0.096)	(0.012)	(0.012)	(0.012)	(0.231)	(0.025)	(0.025)	(0.024)
One-year	-0.056	0.073***	0.072***	0.064***	-0.614***	-0.242***	-0.239***	-0.237***
	(0.096)	(0.013)	(0.013)	(0.013)	(0.229)	(0.023)	(0.023)	(0.023)
Three-year	-0.057	0.071***	0.068***	0.058***	-0.643***	-0.265***	-0.263***	-0.262***
	(0.096)	(0.014)	(0.014)	(0.014)	(0.230)	(0.023)	(0.023)	(0.022)
Five-year	-0.030	0.076***	0.073***	0.061***	-0.639***	-0.276***	-0.279***	-0.279***
	(0.096)	(0.014)	(0.014)	(0.014)	(0.229)	(0.024)	(0.023)	(0.023)
Unspecified	-0.071	0.066***	0.064***	0.054***	-0.556**	-0.213***	-0.206***	-0.207***
	(0.096)	(0.015)	(0.015)	(0.015)	(0.230)	(0.024)	(0.024)	(0.024)
User FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Date FE	No	No	Yes	Yes	No	No	Yes	Yes
Stock FE	No	No	No	Yes	No	No	No	Yes
R-squared Adj.	0.000	0.152	0.167	0.175	0.021	0.210	0.220	0.222
Obs.	419,579	419,579	419,579	419,579	419,579	419,579	419,579	419,579

Table A4: Belief by Horizon around Earnings Announcement. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable for positive and negative earnings announcements (EA), respectively, using the following specification:

$$Outperform_{i(k,t)}(h) = b_1 Positive\ EA_{k,t} + b_2 Negative\ EA_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Standard errors, reported in parentheses, are double clustered by stock and day.

	Outperform$_{i,k,t}$ (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Positive EA	2.980***	1.361*	0.399	-0.585	-0.556**
	(0.816)	(0.724)	(0.524)	(0.431)	(0.248)
Negative EA	-4.155***	-2.034**	-3.078***	-0.381	-0.797**
	(1.227)	(1.017)	(0.650)	(0.570)	(0.351)
1 wk before Positive EA	1.788***	0.302	0.337	0.297	0.012
	(0.578)	(0.386)	(0.284)	(0.215)	(0.134)
1 wk after Positive EA	0.992**	1.261***	1.290***	0.635***	0.688***
	(0.474)	(0.354)	(0.259)	(0.202)	(0.155)
1 wk before Negative EA	-0.226	-0.885	-0.605*	0.063	-0.418*
	(0.748)	(0.579)	(0.367)	(0.324)	(0.218)
1 wk after Negative EA	-2.427***	-1.708***	-1.355***	0.092	-0.046
	(0.721)	(0.569)	(0.383)	(0.281)	(0.209)
Abn. Ret (t-5 to t-1)	5.452***	16.419***	9.339***	4.733***	3.346***
	(1.536)	(2.794)	(1.398)	(0.904)	(0.887)
Abn. Ret (t-25 to t-6)	2.418**	4.831***	2.392***	-0.923	-0.815
	(0.963)	(0.854)	(0.815)	(0.578)	(0.593)
Volatility (t-5 to t-1)	-15.481***	-22.228***	-27.438***	-22.123***	-41.479***
	(4.641)	(6.743)	(5.139)	(3.533)	(3.836)
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
% Outperform Predictions	64.96	72.17	80.77	91.01	87.64

Table A5: Standardized Sentiment by Horizon around Earnings Announcement. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable for positive and negative earnings announcements (EA), respectively, using the following specification:

$$Sentiment_{i(k,t)}(h) = b_1 Positive\ EA_{k,t} + b_2 Negative\ EA_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Sentiment_{i(k,t)}$ equals 1 (-1) for predictions that the focal stock will outperform (underperform) the market and is then normalized to unit variance to facilitate comparison. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Standard errors, reported in parentheses, are double clustered by stock and day.

	Sentiment (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Positive EA	0.062***	0.030*	0.010	-0.020	-0.017**
	(0.017)	(0.016)	(0.013)	(0.015)	(0.008)
Negative EA	-0.087***	-0.045**	-0.078***	-0.013	-0.024**
	(0.026)	(0.023)	(0.016)	(0.020)	(0.011)
1 wk before Positive EA	0.037***	0.007	0.009	0.010	0.000
	(0.012)	(0.009)	(0.007)	(0.008)	(0.004)
1 wk after Positive EA	0.021**	0.028***	0.033***	0.022***	0.021***
	(0.010)	(0.008)	(0.007)	(0.007)	(0.005)
1 wk before Negative EA	-0.005	-0.020	-0.015*	0.002	-0.013*
	(0.016)	(0.013)	(0.009)	(0.011)	(0.007)
1 wk after Negative EA	-0.051***	-0.038***	-0.034***	0.003	-0.001
	(0.015)	(0.013)	(0.010)	(0.010)	(0.006)
Abn. Ret (t-5 to t-1)	0.114***	0.366***	0.237***	0.165***	0.102***
	(0.032)	(0.062)	(0.035)	(0.032)	(0.027)
Abn. Ret (t-25 to t-6)	0.051**	0.108***	0.061***	-0.032	-0.025
	(0.020)	(0.019)	(0.021)	(0.020)	(0.018)
Volatility (t-5 to t-1)	-0.324***	-0.496***	-0.696***	-0.774***	-1.260***
	(0.097)	(0.150)	(0.130)	(0.124)	(0.117)
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828

Table A6: Belief by Horizon around Target Rumors. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable, denoted $Ann_{k,t}$, that captures the presence of rumors about stock k being the target of an acquisition in the news on day t using the following specification:

$$Outperform_{i(k,t)}(h) = b_1 Ann_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Standard errors, reported in parentheses, are double clustered by stock and day.

	Outperform$_{i,k,t}$ (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Ann.	4.596**	3.131**	-1.022	-2.973**	-1.376**
	(2.110)	(1.505)	(1.176)	(1.327)	(0.567)
1 wk before Ann.	0.199	-2.183*	-2.252**	-1.725**	-1.039**
	(1.379)	(1.131)	(0.990)	(0.796)	(0.445)
1 wk after Ann.	-0.773	1.085	-1.310	-1.001	-0.690
	(1.424)	(1.178)	(0.817)	(0.654)	(0.439)
Abn. Ret (t-5 to t-1)	5.955***	16.898***	9.650***	4.740***	3.355***
	(1.571)	(2.732)	(1.422)	(0.898)	(0.885)
Abn. Ret (t-25 to t-6)	2.500***	4.895***	2.459***	-0.898	-0.793
	(0.964)	(0.855)	(0.816)	(0.578)	(0.593)
Volatility (t-5 to t-1)	-15.960***	-22.499***	-26.826***	-20.993***	-40.702***
	(4.667)	(6.548)	(5.067)	(3.467)	(3.763)
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
% Outperform Predictions	64.96	72.17	80.77	91.01	87.64

Table A7: Standardized Sentiment by Horizon around Target Rumors. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable, denoted $Ann_{k,t}$, that captures the presence of rumors about stock k being the target of an acquisition in the news on day t using the following specification:

$$Sentiment_{i(k,t)}(h) = b_1 Ann_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Sentiment_{i(k,t)}$ equals 1 (-1) for predictions that the focal stock will outperform (underperform) the market and is then normalized to unit variance to facilitate comparison. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Standard errors, reported in parentheses, are double clustered by stock and day.

	Sentiment (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Ann.	0.096**	0.070**	-0.026	-0.104**	-0.042**
	(0.044)	(0.034)	(0.030)	(0.046)	(0.017)
1 wk before Ann.	0.004	-0.049*	-0.057**	-0.060**	-0.032**
	(0.029)	(0.025)	(0.025)	(0.028)	(0.014)
1 wk after Ann.	-0.016	0.024	-0.033	-0.035	-0.021
	(0.030)	(0.026)	(0.021)	(0.023)	(0.013)
Abn. Ret (t-5 to t-1)	0.125***	0.377***	0.245***	0.166***	0.102***
	(0.033)	(0.061)	(0.036)	(0.031)	(0.027)
Abn. Ret (t-25 to t-6)	0.052***	0.109***	0.062***	-0.031	-0.024
	(0.020)	(0.019)	(0.021)	(0.020)	(0.018)
Volatility (t-5 to t-1)	-0.335***	-0.502***	-0.681***	-0.734***	-1.237***
	(0.098)	(0.146)	(0.129)	(0.121)	(0.114)
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828

Table A8: Belief by Horizon around Technical Views. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable, denoted $Ann_{k,t}$, that captures the presence of rumors about stock k's acquisition in the news on day t using the following specification:

$$Outperform_{i(k,t)}(h) = b_1\, Technical\ View\ Ann_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Outperform_{i(k,t)}$ is a dummy variable multiplied by 100 for predictions that the focal stock will outperform the market. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Panel A shows results for a bullish technical view, and Panel B shows results for a bearish technical view. Standard errors, reported in parentheses, are double clustered by stock and day.

	Outperform$_{i,k,t}$ (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Panel A: Bullish Technical View					
Ann.	3.506***	1.963***	0.746	0.627	1.277***
	(0.805)	(0.702)	(0.571)	(0.433)	(0.209)
1 wk before Ann.	2.600***	1.266	2.234***	1.147***	1.229***
	(0.890)	(0.905)	(0.559)	(0.426)	(0.223)
1 wk after Ann.	2.232***	1.801***	1.334***	0.940***	1.229***
	(0.539)	(0.467)	(0.368)	(0.295)	(0.187)
Abn. Ret (t-5 to t-1)	5.668***	16.646***	9.608***	4.692***	3.170***
	(1.552)	(2.808)	(1.408)	(0.900)	(0.886)
Abn. Ret (t-25 to t-6)	2.512***	4.879***	2.466***	-0.901	-0.810
	(0.967)	(0.855)	(0.819)	(0.580)	(0.596)
Volatility (t-5 to t-1)	-15.795***	-21.980***	-27.047***	-21.306***	-40.734***
	(4.677)	(6.763)	(5.066)	(3.473)	(3.756)
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
% Outperform Predictions	64.96	72.17	80.77	91.01	87.64
Panel B: Bearish Technical View					
Ann.	-3.245***	-3.218***	-0.401	0.961*	0.381
	(1.064)	(0.859)	(0.602)	(0.526)	(0.252)
1 wk before Ann.	-2.410**	-0.282	-0.513	0.503	0.332
	(0.969)	(0.910)	(0.586)	(0.437)	(0.217)
1 wk after Ann.	-2.945***	-0.322	-0.533	0.337	0.547***
	(0.598)	(0.600)	(0.387)	(0.338)	(0.196)
Abn. Ret (t-5 to t-1)	5.681***	16.706***	9.675***	4.827***	3.444***
	(1.552)	(2.816)	(1.413)	(0.902)	(0.887)
Abn. Ret (t-25 to t-6)	2.397**	4.867***	2.444***	-0.871	-0.749
	(0.961)	(0.854)	(0.819)	(0.579)	(0.595)
Volatility (t-5 to t-1)	-15.731***	-22.047***	-27.106***	-21.382***	-41.010***
	(4.679)	(6.783)	(5.075)	(3.467)	(3.767)
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
% Outperform Predictions	64.96	72.17	80.77	91.01	87.64
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes

Table A9: Standardized Sentiment by Horizon around Technical Views. The table shows the results from regressing user i's forecast about stock k on day t for a given horizon h on a dummy variable, denoted $Ann_{k,t}$, that captures the presence of rumors about stock k's acquisition in the news on day t using the following specification:

$$Sentiment_{i(k,t)}(h) = b_1 \, Technical \;\; View \;\; Ann_{k,t} + \mathbf{\Gamma X} + \alpha_i + \nu_k + \gamma_t + \epsilon_{i,k,t}.$$

$Sentiment_{i(k,t)}$ equals 1 (-1) for predictions that the focal stock will outperform (underperform) the market and is then normalized to unit variance to facilitate comparison. $\mathbf{X}$ includes dummy variables for one week before the announcement, one week after the announcement, Abn. Ret ($t-5$ to $t-1$), Abn. Ret ($t-20$ to $t-6$), and Volatility ($t-5$ to $t-1$). The regression is estimated separately for each horizon h indicated in the column headers. Panel A shows results for a bullish technical view, and Panel B shows results for a bearish technical view. Standard errors, reported in parentheses, are double clustered by stock and day.

	Sentiment (h)				
	Three-week	Three-month	One-year	Three-year	Five-year
Panel A: Bullish Technical View					
Ann.	0.073***	0.044***	0.019	0.022	0.039***
	(0.017)	(0.016)	(0.014)	(0.015)	(0.006)
1 wk before Ann.	0.055***	0.028	0.057***	0.040***	0.037***
	(0.019)	(0.020)	(0.014)	(0.015)	(0.007)
1 wk after Ann.	0.047***	0.040***	0.034***	0.033***	0.037***
	(0.011)	(0.010)	(0.009)	(0.010)	(0.006)
Abn. Ret (t-5 to t-1)	0.119***	0.371***	0.244***	0.164***	0.096***
	(0.033)	(0.063)	(0.036)	(0.031)	(0.027)
Abn. Ret (t-25 to t-6)	0.053***	0.109***	0.063***	-0.032	-0.025
	(0.020)	(0.019)	(0.021)	(0.020)	(0.018)
Volatility (t-5 to t-1)	-0.331***	-0.490***	-0.686***	-0.745***	-1.238***
	(0.098)	(0.151)	(0.129)	(0.121)	(0.114)
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
Panel B: Bearish Technical View					
Ann.	-0.068***	-0.072***	-0.010	0.034*	0.012
	(0.022)	(0.019)	(0.015)	(0.018)	(0.008)
1 wk before Ann.	-0.051**	-0.006	-0.013	0.018	0.010
	(0.020)	(0.020)	(0.015)	(0.015)	(0.007)
1 wk after Ann.	-0.062***	-0.007	-0.014	0.012	0.017***
	(0.013)	(0.013)	(0.010)	(0.012)	(0.006)
Abn. Ret (t-5 to t-1)	0.119***	0.373***	0.245***	0.169***	0.105***
	(0.033)	(0.063)	(0.036)	(0.032)	(0.027)
Abn. Ret (t-25 to t-6)	0.050**	0.109***	0.062***	-0.030	-0.023
	(0.020)	(0.019)	(0.021)	(0.020)	(0.018)
Volatility (t-5 to t-1)	-0.330***	-0.492***	-0.688***	-0.748***	-1.246***
	(0.098)	(0.151)	(0.129)	(0.121)	(0.114)
R-squared Adj.	0.365	0.392	0.405	0.348	0.395
Obs.	160,152	265,231	448,034	336,366	1,404,828
User FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes

C Topic-specific Dictionaries and Pitch Loadings

This section describes the steps used in constructing dictionaries for the long-term, short-term, fundamental and technical analysis topics, respectively. It also describes how we quantify the loading of each pitch on a given topic's dictionary. Our implementation steps follow Li, Mai, Shen, and Yan (2021), who develop dictionaries for corporate culture.

To construct the dictionary that captures the words that best reflect a given topic, we start with seed words for each topic, then apply word embeddings and cosine similarity. Word embeddings learn the meaning of a word or phrase based on its context and then represent a word's meaning using a numeric vector. The embedding model we use is *word2vec* (Mikolov, Sutskever, Chen, Corrado, and Dean, 2013), which uses a neural network to learn dense and low-dimensional vectors representing word meanings. The model can then predict similar words for a given focal word using the contextual information embedded in the model.

To train the *word2vec* model on our pitch corpus, we first process the raw text data using the following steps: (i) Apply sentence segmentation and tokenization, as word2vec operates at the sentence level. (ii) Apply lemmatization and normalization to reduce words to their base forms and lowercase. (iii) Apply named entity recognition to replace names of organizations, people, places and numbers with generic tags to reduce noise. We retain numbers that are followed by terms such as day, quarter, year, etc., as those indicate periods that are relevant for certain topics we are interested in. (iv) We remove punctuation marks, stop words, and single letter words, then concatenate common two-word phrases to single words by using the underscore symbol "_" in place of spaces (e.g., "rather than" becomes "rather_than").

Next, we set the dimension of word vectors to 300, define two words as neighbors if they are no farther apart than five words in a sentence, and exclude words that appear less than 50 times in our text corpus. For the hyperparameters, we set the window size to five, the number of iterations over the corpus to 20, and use the skip-gram with negative sampling method (SGNS) as the training method.

We proceed as follows to obtain a dictionary for each topic from the trained *word2vec* model. First, we define seed words for each topic $\mathcal{N}$. The seed words for the "long-term" topic are *long_term, longrun, lt*, and *long_haul*. The seed words for the "short-term" topic are *short_term, near_term, shortrun, temporary*, and *few_month*. The seed words for the "fundamental" topic are *fundamental, cash_flow, balance_sheet, debt, income_statement, current_ratio, roe_and_roa, cash_on_hand*, and *capital_structure*. The seed words for the "technical analysis" topic are *momentum, pull_back, technical_analysis, ema_cross, oscillator, rsi, moving_average, macd_and_directional*, and *resistance_level*.

Next, we obtain the word vector for each seed word and then average the seed words' vectors to obtain an average seed vector $\overline{V}_{\mathcal{N}}$ for the topic. We compute the cosine similarity between the vector of each unique word in the pitches with $\overline{V}_{\mathcal{N}}$ and select the top 100 words with the largest cosine similarity score. If a word appears in both the long-term and short-term topics' dictionaries, we include it in the dictionary for which it has the highest cosine similarity score. We do the same for words that simultaneously appear in both the fundamental and technical analysis dictionaries. Table 2 shows the words in each dictionary.