Optimism Shifting*

Stefano Cassella† Chukwuma Dim‡ Tural Karimli§

This version: March, 2024

Abstract

Forecasters who are optimistic about an asset react to negative news by shifting their optimistic expectations to a longer forecast horizon. To document this novel pattern of optimism shifting in belief updating we rely on CAPS, a social-finance platform offering the unique opportunity to observe individuals' beliefs about stocks alongside their chosen forecast horizon. Additional analysis indicates that optimism shifting leads to large underperformance, and it is consistent with forecasters' motivation to retain optimistic beliefs about their skill (confidence channel), the value of their financial assets (financial-stakes channel), and the value of their accrued knowledge about an asset (intangible-stakes channel).

Keywords: Belief Updating, Individual Investors, Social Finance, Motivated Beliefs, Term-structure, Expectations

JEL: G40, D83, D84

*We are grateful to Turan Bali, Andrew Chen, Tony Cookson, Julio Crego, Francesco D'Acunto, Jesse Davis, Joost Driessen, Sebastian Ebert, Clifton Green, Amit Goyal, Huseyin Gulen, Gergana Jostova, Badri Kottimukkalur, Yueran Ma, Will Mullins, Nicola Pavanini, Kim Peijnenburg, Lin Peng, Vincenzo Pezone, Veronika Pool, Alberto Rossi, Christoph Schiller, Grigory Vilkov and seminar participants at the Stigler Center Affiliate Fellows Conference at the University of Chicago Booth, the University of Pisa, and the 2024 Midwest Finance Association (MFA) conference for their helpful comments and suggestions. We are especially grateful to the MFA selection committee for giving this paper the Best Paper Award in Investments and Asset Pricing.

†Tilburg University ✉ s.cassella@tilburguniversity.edu.
‡George Washington University ✉ cdim@gwu.edu.
§Frankfurt School of Finance & Management ✉ t.karimli@fs.de.

Optimism Shifting

This version: March, 2024

Abstract

Forecasters who are optimistic about an asset react to negative news by shifting their optimistic expectations to a longer forecast horizon. To document this novel pattern of optimism shifting in belief updating we rely on CAPS, a social-finance platform offering the unique opportunity to observe individuals' beliefs about stocks alongside their chosen forecast horizon. Additional analysis indicates that optimism shifting leads to large underperformance, and it is consistent with forecasters' motivation to retain optimistic beliefs about their skill (confidence channel), the value of their financial assets (financial-stakes channel), and the value of their accrued knowledge about an asset (intangible-stakes channel).

Keywords: Belief Updating, Individual Investors, Social Finance, Motivated Beliefs, Term-structure, Expectations

JEL: G40, D83, D84

1 Introduction

In standard theories of belief formation, individuals acquire and process all available information rationally to form accurate and unbiased expectations about uncertain future outcomes. Work on motivated beliefs and belief-based utility challenges this view (Brunnermeier and Parker, 2005; Bénabou and Tirole, 2016; Caplin and Leahy, 2019). This work posits that when individuals gain utility from the anticipation of positive future experiences, a strong motive arises to manipulate the belief formation process so as to maintain self-serving optimistic beliefs about one's future well-being.[1]

A key question in the extant literature on motivated beliefs is how people can hold on to self-serving optimistic expectations of future job outcomes, health, or the return from risky investments in the face of incoming disconfirming news. Past contributions primarily emphasize the role of distortions in information acquisition or recall (e.g., Golman et al., 2017; Bénabou, 2015; Zimmermann, 2020; Amelio and Zimmermann, 2023): agents can stay optimistic by avoiding the acquisition of new information, or through the selective recall of good past events from memory. Importantly, avoiding or selectively recalling information is a costly strategy. This strategy is likely to be viable in contexts where feedback is limited or infrequent (e.g., in the domain of health expectations Oster et al., 2013), but it can be extremely costly in settings such as equity investments, where current and past information on investment performance is delivered at all times via multiple means (TV, newspapers, social media, and trading apps).[2] If avoiding negative information in the stock market is excessively costly, can motivated beliefs still be relevant for expectations about stock investments?

In this paper, we argue that although information avoidance can be difficult in the stock market, investors can form and maintain motivated beliefs about stocks due to the selective interpretation of incoming information. In particular, we demonstrate a novel mechanism of strategic information interpretation that we term *optimism shifting*. We show that optimism

[1] For more theoretical work on belief-based utility, see Akerlof and Dickens (1982); Loewenstein (1987); Caplin and Leahy (2001); Eliaz and Spiegler (2006); Bénabou (2013, 2015). For empirical evidence, see Weinstein (1980); Scheier and Carver (1985); Puri and Robinson (2007); Oster et al. (2013); Zimmermann (2020); Cassella et al. (2023).

[2] See Karlsson et al. (2009) for evidence of selective attention to news in financial markets. See also Cookson et al. (2023) for evidence that, in social platforms, investors engage in the strategic avoidance of out-group beliefs.

shifting strongly contributes to investors' ability to maintain self-serving motivated optimism about the value of an asset in the face of negative information about that asset.

Simply put, when investors form beliefs about the future value of a stock, they not only choose whether to be optimistic or not about the stock but also at what horizon. Whereas investors may prefer, everything else equal, to believe that their investment in a stock will be successful in the near future, widespread negative news about the stock can arrive that can be costly to ignore or avoid. In such a setting, investors can hold on to their optimism by selectively interpreting the incoming negative news as relevant only for the short run but not the longer horizon, leading to the shifting of one's optimistic expectation from a shorter to a longer horizon. Such optimism shifting can serve as a tool for investors to maintain optimistic beliefs even when it is difficult or impossible to avoid negative information.

Testing the optimism-shifting hypothesis in financial markets is difficult. A laboratory experiment generally offers a cleaner setup than does working with observational data. However, we are interested in whether investors engage in optimism shifting in the complex information environment they face when making real-world financial decisions. At the same time, using real-world trading data (e,g., Odean, 1998c; Barber and Odean, 2000) is unattractive for studying optimism shifting because, in the face of negative news, optimism shifting would result in investors sticking to their portfolios. Such a seeming lack of reaction to the news would, in turn, be difficult to link to optimism shifting, as opposed to other mechanisms such as trading inertia, inattention, or information avoidance.

We circumvent these empirical challenges by relying on direct data on investor beliefs from CAPS, a social finance forum. Since 2006, CAPS has collected over 5.4 million predictions on roughly 9,500 stocks from a broad sample of over 190,000 individual investors. Participants on the platform submit beliefs on whether a stock will outperform or underperform the S&P 500 index. Other social-finance platforms similar to CAPS exist, such as Stocktwits (e.g., Cookson et al., 2023; Cookson and Niessner, 2020), Forcerank (e.g., Da et al., 2021), or Seeking Alpha (e.g., Farrell et al., 2021; Dim, 2020; Chen et al., 2014). However, these other platforms collect beliefs without requiring a prediction horizon or only allowing for a fixed horizon. In contrast, CAPS requires participants to specify the horizon (from three weeks to five years) a forecast refers to, making CAPS a natural setting to study the term structure of beliefs.

While CAPS allows individuals to submit multiple predictions for different stocks simultaneously, the platform restricts a forecaster's number of active predictions for any given stock to one. Consequently, to engage in optimism shifting following negative news, a forecaster with an outstanding prediction has to actively terminate the existing prediction and initiate a new prediction over the new desired horizon. This key feature of our data allows us to measure optimism shifting based on active forecasters' decisions.

Finally, whereas institutional incentives can create a difference between forecasts and true beliefs among professional forecasters,[3] this wedge is likely absent in our setting, since CAPS participants use pseudonyms and are not professionals. Importantly, CAPS does incentivize forecast accuracy by publishing rankings based on such accuracy. However, these rankings are only based on whether the performance of a stock aligns with a forecaster's prediction, irrespective of the forecaster's stated forecast horizon. This is an ideal setting to study optimism shifting, since by neglecting the horizon of the predictions, CAPS-based incentives neither induce nor constrain forecasters' choice of a prediction horizon or the optimism shifting.

We begin our analysis by showing that beliefs elicited through CAPS are more likely to be optimistic (pessimistic) following good (bad) stock returns, consistent with the recent evidence that past returns shape investor beliefs (e.g., Da et al., 2021).[4] It is this insight, and the fact that recent stock returns are made salient on CAPS, that prompts us to use past stock returns as a readily available measure for news about a stock in our main analysis.[5] Using our return-based news metric, we study belief-update events, i.e., events in which a forecaster with an outstanding prediction about a stock ends his prediction following the arrival of news about the stock and initiates a new prediction shortly after.

[3]For instance, sell-side analysts can display excessive optimism about the prospects of a firm to curry favor with the firm's management (e.g., Lin and McNichols, 1998; Michaely and Womack, 1999).

[4]We also document that the beliefs are generally optimistic and that optimism increases with horizon, complementing earlier evidence on optimism bias (Puri and Robinson, 2007; Oster et al., 2013; Cassella et al., 2022, 2023).

[5]We also repeat the analysis using earnings surprises and document qualitatively similar results.

We first document that optimistic and pessimistic forecasters react to news differently, with the former exhibiting lower sensitivity to negative news than the latter.[6] We then show strong evidence of optimism shifting: the relative insensitivity to negative news that is observed among optimistic forecasters grows roughly twofold among those who, when revising their prediction, choose a new forecast horizon that is longer than the previous one.

The results are robust to the inclusion of investor fixed effects, meaning that our evidence captures how the same individual will respond differently to negative news versus good news about a stock depending on their prior belief. The optimism shifting evidence is also robust to the inclusion of stock $\times$ time fixed effects, allowing us to compare the behavior of two forecasters, one previously optimistic and one previously pessimistic, in response to the same negative news about the same stock. We also conduct several robustness tests using alternative news measures and expectation horizon definitions. The results are also robust to using an instrumental-variable procedure to address the simultaneity of the belief and horizon choices, thereby boosting the interpretation that horizon choice has a causal role in belief updating. Finally, we replicate and provide external validity for our findings using data from Seeking Alpha (SA), another social finance platform. Although forecasters' views about stocks on SA do not have explicit expectation horizons, we apply natural language processing techniques to indirectly quantify forecasters' horizons based on the arguments used to support their predictions. We then show that our main results hold in this setting. Overall, the evidence strongly suggests that optimism shifting is a systematic and robust pattern in agents' belief formation about risky assets.

Next, we conduct tests to gauge the link between motivated beliefs and optimism shifting. We draw on three theoretical insights from the literature. First, Bénabou (2015) argues that distortions in expectations that are due to motivated beliefs should be larger for outcomes an agent has a large exposure to. Therefore, if optimism shifting stems from motivated beliefs, we expect it to be stronger among stocks that retail investors such as the ones who submit

[6] The fact that a public negative signal can lead individuals with different prior beliefs to update differently is not new. Rather, it resonates with the extant literature that ascribes similar patterns to the role of confirmation bias in belief updating. Confirmation bias induces individuals with optimistic (pessimistic) beliefs about an outcome to selectively interpret incoming information so as to maintain their existing optimistic (pessimistic) beliefs. See, Lord et al. (1979); Darley and Gross (1983); Rabin and Schrag (1999); Fryer Jr et al. (2019); Rabin and Schrag (1999).

forecasts on CAPS are more likely to own (Barber and Odean, 2000, 2001; Mitton and Vorkink, 2007; Kumar, 2009). Second, Caplin and Leahy (2019) argue that the distortions in beliefs that are due to motivated beliefs are larger when evaluating more uncertain gambles. Intuitively, in such settings, it is easier to entertain one's desired optimistic belief about a stock's prospects. Third, Brunnermeier and Parker (2005) argue that motivated optimism about the value of an asset should increase when the asset has a more positively skewed payoff. Collectively, these theories suggest that a stronger optimism shifting should be observed among small, low-price, high-volatility, illiquid stocks with lottery-like payoffs. Accordingly, we find that optimism shifting is very strong for these stocks and much smaller or absent for other stocks.

In addition to the analysis above, we also note that an agent's exposure to a stock need not be due to financial ownership of the stock. In particular, recent work has begun to uncover the large value attached to intangible assets such as knowledge. Veldkamp (2023) defines knowledge as the result of analyzing raw data to make predictions. In the process of making forecasts about a firm, a forecaster accumulates knowledge about a firm. The value of knowledge in the firm is likely to be contingent on the firm's future performance, particularly when knowledge is firm-specific. In such instances, if the firm experiences distress or goes out of business, the value of the accumulated knowledge can be greatly diminished. Thus, this knowledge-based channel suggests that optimism shifting should be more pronounced for stocks whose valuation is driven more by firm-specific information. Consistent with the hypothesized knowledge-based driver, we find that optimism shifting is particularly strong and highly statistically significant in the sample of firms whose valuation has a large firm-specific component.[7]

Finally, following the literature, we argue that optimism shifting can be due to ego-utility, a form of motivated belief where agents prefer to retain a positive self-image.[8] When a forecaster is optimistic about a stock, the arrival of negative news about that stock threatens the fore-

[7]Following Chen et al. (2007), we measure the extent of firm-specific information from a regression of stock returns on the market and an industry factor. This metric is related to, but distinct from, idiosyncratic volatility. Idiosyncratic volatility explains only around 14% of the variation in the Chen et al. (2007) firm-specific information metric in our sample. We also conduct a second test of the knowledge channel of optimism shifting based on the comparison between forecasters who are focused on the industry of the focal stock, and the ones who do not. The results are consistent with a knowledge channel of optimism shifting. We present these results in Section 5.2.

[8]A conviction in one's ability has several advantages, including increased perseverance in difficult or risky tasks (Schulz et al., 1999; Bénabou and Tirole, 2002), attainment of strategic advantage in competitive tasks (Johnson and Fowler, 2011; Charness et al., 2018), and ability to influence and convince others (Von Hippel and Trivers, 2011).

caster's self-image and perception of ability to make correct forecasts. Optimism shifting could arise to protect the forecaster's positive self-view. Notably, theory work by Köszegi (2006) suggests that individuals with a strong self-image are more likely to engage in self-image protection. Thus, we examine how optimism shifting varies across forecasters' perceived self-image (ability to make correct forecasts), measured based on CAPS forecaster ranking. We find that optimism shifting roughly doubles for the high-ranked forecasters, while there is no statistical evidence of optimism shifting for the low-ranked ones. However, the evidence of a statistical difference between optimism shifting among the high and low-ranked individuals is mixed.

Although our proposed explanation is that optimism shifting stems from motivated beliefs, we also investigate whether our evidence could be consistent with rational expectations, or with theories of extrapolation and diagnostic beliefs that have garnered considerable attention in the recent literature, or whether it might be due to heterogeneity in priors between optimists and pessimists. Our analysis provides little support for these alternative explanations.

In the last part of the paper, we examine the implications of optimism shifting for investment performance. We compare the abnormal return of a forecaster who is optimistic, receives negative news, and then engages in optimism shifting to that of an optimist who does not engage in optimism shifting following negative news. Across specifications, we consistently find that optimism shifting leads to subsequent underperformance ranging from -5% to -7% abnormal returns over a 3-month and 1-year window, respectively.

Our contribution is to the behavioral finance literature. In this literature, a large body of work documents patterns of over-reaction and under-reaction in beliefs that have been linked to exogenous features of the information environment or to endowed cognitive limitations and bounded rationality.[9] This literature has so far only made limited use of insights from theories of motivated beliefs, in which distortions in expectations arise endogenously due to the utility individuals derive from the anticipation of future experiences. Few papers have studied experimentally whether individuals update beliefs asymmetrically following good versus bad news, offering mixed evidence (Eil and Rao, 2011; Kuhnen, 2015; Charness and Dave, 2017; Hartzmark et al., 2021; Möbius et al., 2022). A paper close to ours is Zimmermann (2020), which

[9] E.g., theories of noisy information (Woodford, 2001), costly information acquisition, (Mankiw and Reis, 2002) or belief formation under representativeness (Barberis et al., 2015; Bordalo et al., 2018; Afrouzi et al., 2020).

studies how motivated beliefs are maintained in the face of incoming news. However, they focus on how distortions in recall from memory fuel motivated beliefs, and their lab experiments are not about financial investments. In contrast, we study a different and, to the best of our knowledge, novel mechanism for motivated beliefs in financial markets, termed optimism shifting.

In focusing on stock investing, our paper joins a small literature on motivated beliefs in financial markets. Brunnermeier and Parker (2005) show how motivated beliefs can arise when a financial asset has an uncertain, positively skewed payoff. Cassella et al. (2021) empirically link motivated beliefs to the term structure of equity returns. Most related to our paper in this literature is Banerjee et al. (2023), which shows theoretically that investors in financial markets can dismiss a public signal about firm value as uninformative due to motivated beliefs. We complement this work by showing empirically that, due to motivated beliefs, investors regard incoming negative news as only informative about short-term stock performance, dismissing its informativeness for long-term performance.

Our analysis of the implications of knowledge for optimism shifting also contributes to a new literature that examines the properties and the valuation of intangible capital (Eisfeldt and Papanikolaou, 2014, Crouzet et al., 2022, Veldkamp and Chung, 2019, Veldkamp, 2023). This literature has so far focused on valuing the acquisition and processing of data under rational expectations. Our work indicates that knowledge about a firm can have important behavioral implications for beliefs beyond the rational expectations paradigm.[10]

Our paper joins a growing literature on social finance (e.g., Chen et al., 2014; Avery et al., 2016; Heimer, 2016; Cookson and Niessner, 2020; Dim, 2020; Farrell et al., 2021; Da et al., 2021; Bradley et al., 2021; Cookson et al., 2022; Kakhbod et al., 2023; Levy et al., 2023; Hirshleifer et al., 2023). A paper related to ours is Cookson et al. (2023). They demonstrate that investors choose their connections on social forums to shield themselves from disconfirming news. While their evidence is consistent with individuals' preference to maintain their pre-existing beliefs, our optimism-shifting evidence speaks more directly to how individuals protect their existing views even when they cannot avoid incoming news.

[10]Insofar as optimism shifting is an unintended byproduct of knowledge, our paper relates to those cautioning that more knowledge does not always lead to better decisions (e.g., Camerer et al., 1989, Banerjee et al., 2020).

2 Data and Summary Statistics

This section describes the CAPS platform and the data we obtained from the platform. It also presents the summary statistics of the main variables, while Table A1 describes the construction of the variables used for the analysis.

2.1 CAPS System Data

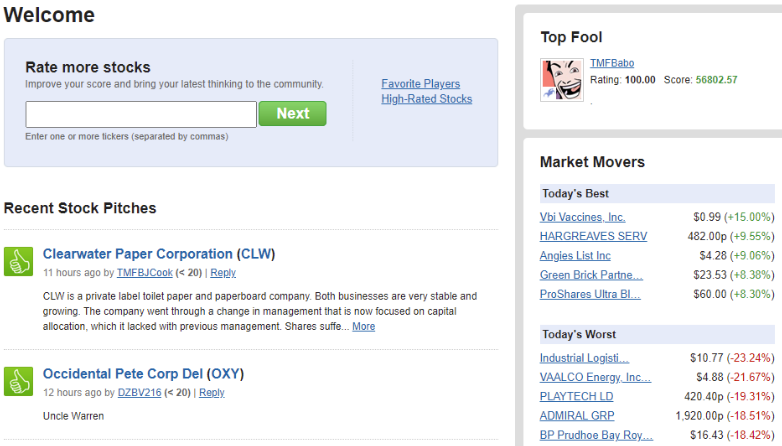
CAPS is a social media platform focused on stock prediction. The platform is managed by Motley Fool, an online financial advisory firm providing investment advice, stock recommendations, and financial planning services. CAPS is freely accessible to anyone who wants to express beliefs about the future return performance of specific stocks. Figure 1, Panel A, depicts a user's homepage on CAPS, inviting the individual to make a prediction. To express beliefs on CAPS, an individual chooses a stock ticker from a list of eligible tickers. To be eligible for predictions on CAPS, a stock must have an average daily trading volume of $50,000 or more over the preceding quarter, as well as a previous-day trading volume above the same threshold. Moreover, the current stock price must be above $1.50. These restrictions aim to eliminate predictions on very illiquid and small stocks.

Figure 1, Panel B shows the CAPS prediction page where the individual enters his expectation of a stock's future return. When submitting a forecast about a stock on CAPS, the platform displays the stock's current price, the stock's return relative to the previous market close, and the stock exchange where the stock is trading.[11] Similar to other social finance platforms, a participant on CAPS enters a prediction of whether a stock will *outperform* or *underperform* the S&P 500 index. Unlike other platforms, CAPS also asks forecasters to indicate the horizon their prediction refers to using the following options: three-week, three-month, one-year, three-year, or five-year period. Importantly, whereas an individual can have multiple active predictions for different stocks simultaneously, he can have only one active prediction per stock. So, should a CAPS forecaster want to change the direction of his existing prediction about a stock, the pre-

[11] The user may also specify "Start Limit", which is the price at which prediction should become active, "Upper Close Limit" and "Lower Close Limit", which are the maximum and minimum prices, respectively, after which the prediction should be closed. In practice, we do not observe whether these fields are populated and thus are not used in our analysis.

diction horizon, or both, he has to terminate the existing forecast and initiate a new one with the revised prediction and horizon.

A: User Homepage



B: Stock Prediction Page

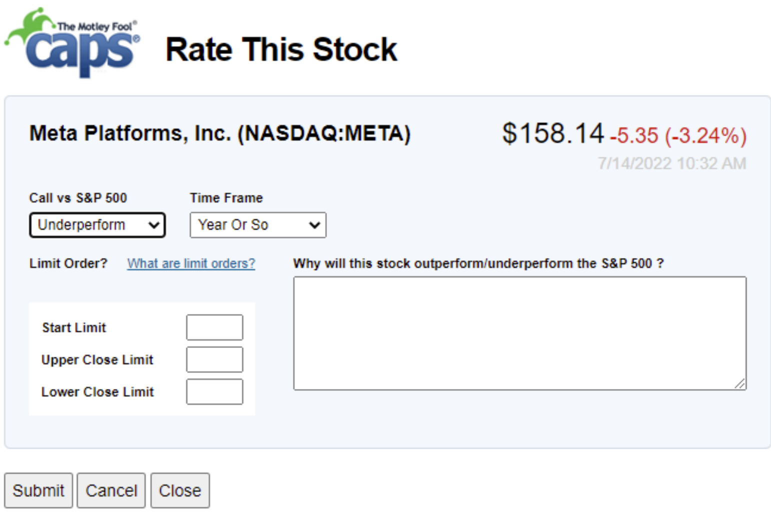


Figure 1: Example of CAPS User Homepage and Stock Prediction Page. This figure presents the screenshot of a CAPS user homepage in Panel A, inviting the user to make a prediction about a stock. Panel B shows the stock prediction page after the user has entered a stock ticker and clicked the "Next" button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

Studying beliefs is difficult in the presence of strategic incentives because such incentives can lead forecasters to make predictions that differ from their true expectations (e.g., sell-side analysts, Jackson, 2005; Lim, 2001; Michaely and Womack, 1999). This is not a reason for concern in CAPS since individuals making predictions on CAPS do not receive any financial compensation from the platform. Such a lack of financial incentives, jointly with the anonymity of the CAPS participants, allows the researcher to study the properties of belief formation without the aforementioned concerns.

While there are no monetary incentives, CAPS does incentivize forecasters to produce accurate forecasts, in that the platform ranks forecasters based on forecast accuracy.[12] Importantly, when ranking forecasters, CAPS does not assess the accuracy of a forecaster's prediction just at the prediction due date. Instead, forecast accuracy is measured in real-time based on whether a stock has outperformed or underperformed the market—measured as the SPDR S&P 500 ETF Trust (SPY) index—on any given day. Effectively, therefore, the forecasters' stated horizons are not shaped by the incentives offered on the platform, meaning that the specific institutional features of CAPS do not shape the prediction horizon choice that is central to our analysis. For this reason, the findings in this paper concerning the role of horizon choice for belief formation are likely to apply to a broader population of investors than just the CAPS participants.[13]

To collect the CAPS data, we develop a web scraping algorithm used to obtain the predictions posted on CAPS over the period April 2006 - December 2022. For each prediction, we retrieve the prediction date, stock ticker, and the horizon of the prediction. We obtain roughly 5.4 million predictions covering roughly 9,500 stocks that we are able to match with the Center for Research in Security Prices (CRSP) PERMNO. These expectations were expressed by a broad sample of roughly 190,000 individuals. We then apply the following filters: (i) keep only ordinary common stocks (share codes 10, 11, 12) to be able to obtain market data and firm fundamentals easily; (ii) keep only individuals with at least seven predictions over the full sample initiated on at least two different days, given that CAPS requires at least seven active predictions to rank a forecaster; (iii) keep individual-day observations with at most 30 new predictions (the 90th percentile of the distribution) to prevent unusual spikes in forecaster

[12]Top forecasters are labeled "Top Fool" and are advertised on the platform: they are offered larger visibility and are assigned an area on the platform to write a brief text addressing the rest of the community. As has been noted for other social finance forums (e.g., Chen et al., 2014; Cookson and Niessner, 2020), key motivations for expressing beliefs on CAPS include deriving fame and satisfaction from ranking highly on the prediction task, learning from the views of peers, and having an objective evaluation of one's own ability to beat the market. The horizon feature of CAPS allows participants to express their expectation horizon, which is an aspect of beliefs that arises naturally in financial market settings.

[13]Later in Section 4.5, we formally show evidence of external validity using alternative data from Seeking Alpha, another social finance platform.

activity from driving our results; (iv) keep only predictions whose stated horizon is not set to indefinite, owing to the ambiguity of such a horizon choice.

With these filters, the final sample amounts to roughly 3.1 million predictions initiated by approximately 75,000 individuals. Out of these predictions, roughly 265,000 (or about 10% of the sample) are part of a belief-update event initiated by roughly 9,000 individuals: these events are cases where a forecaster terminates an existing prediction on a stock and initiates a new one about the same stock within five calendar days. We refer to this subset of updated predictions as the *belief-update sample* in the remainder of the paper.[14]

Table 1 shows summary statistics for our CAPS and belief-update samples. Panel A shows that an average forecaster made a total of 81 predictions and updated 15 of those within five days of terminating the existing prediction. Within the set of forecasters in the belief-update sample, the average forecaster spent roughly 3 years on CAPS and had roughly 97 outstanding (active) predictions on other stocks before initiating the update on the focal stock.

Panel B of Table 1 summarizes the direction of the forecasts on CAPS by looking at the frequency of optimistic predictions. Over the full CAPS sample, 82% of the predictions state that the stock will outperform the market, the average forecaster is optimistic 89% of the time, and the average stock received a 76% average optimism. Overall, the beliefs are very optimistic, in line with the recent literature using data from other social finance forums (e.g., Dim, 2020; Da et al., 2021; Cookson et al., 2023). Panel C of Table 1 describes the frequency of predictions made across the different horizons and the average optimism across the horizons. In the full CAPS sample, the average optimism for the short horizon predictions (three-week to one-year) is 73%, while that for the long horizon predictions (three-year and five-year) is 18% larger at 86%. This pattern aligns with the recent evidence on an upward-sloping term structure of optimism among financial analysts and macroeconomic forecasters (Cassella et al., 2022, 2023).

[14] The fact that roughly 90% of predictions are not part of the belief-update sample does not mean these other predictions are stale. Many predictions do get updated. On the other hand, the distance in time between the termination of a prior prediction and the beginning of a new one may be considerable. A longer time between the end of an old prediction and the beginning of a new one can create a wedge between the pre-existing beliefs expressed in an old prediction and an individual's actual beliefs before the arrival of news and a belief-update event. Moreover, as the distance in time between consecutive predictions increases, it is more difficult to obtain a good proxy for the information that triggers the belief-update event. For this reason, when identifying belief-update events, we concentrate on those belief-update events in which there is a short time window between the termination of an outstanding prediction and the beginning of a new one.

Panel A: Summary of Activity on CAPS							
	Mean	SD	10%	25%	50%	75%	90%
# predictions per forecaster	81	346	8	11	20	51	154
# belief-update per forecaster	15	84	1	1	2	5	21
# predictions per stock	466	1170	10	41	153	446	1037
# belief-update per stock	26	54	1	3	10	27	62
# forecaster outstanding predictions as of belief-update	97	51	18	52	110	139	156
Forecaster CAPS age (years) as of belief-update	3.364	3.588	0.214	0.671	1.953	4.929	8.966

Panel B: Share of Optimistic Predictions							
	Mean	SD	10%	25%	50%	75%	90%
CAPS Sample							
All	0.816	0.387	0.000	1.000	1.000	1.000	1.000
Per forecaster	0.888	0.170	0.667	0.833	0.983	1.000	1.000
Per stock	0.763	0.218	0.436	0.667	0.839	0.918	0.958
Belief-update Sample							
All	0.602	0.490	0.000	0.000	1.000	1.000	1.000
Previously pessimistic	0.169	0.375	0.000	0.000	0.000	0.000	1.000
Previously optimistic	0.884	0.320	0.000	1.000	1.000	1.000	1.000
Per stock	0.627	0.346	0.000	0.333	0.724	0.944	1.000

Panel C: Summary of Prediction Horizons						
	CAPS Sample			Belief-update Sample		
	# Predictions	% Predictions	Ave. Optimism	# Predictions	% Predictions	Ave. Optimism
Three-week	206,491	7	0.638	9,539	7	0.498
Three-month	303,984	10	0.701	11,768	9	0.525
One-year	504,635	16	0.786	16,683	13	0.610
Three-year	372,626	12	0.903	8,287	6	0.823
Five-year	1,705,131	55	0.848	86,228	65	0.606
Total	3,092,867	100		132,505	100	

Panel D: Number of Users by Self-reported Experience				
	CAPS Sample		Belief-update Sample	
	# Forecasters	% Forecasters	# Forecasters	% Forecasters
Low	5,845	8	1,099	12
Medium Low	5,391	7	972	11
Medium	8,016	11	1,584	18
Medium High	3,796	5	815	9
High	2,394	3	658	7
Unspecified	49,147	66	3,826	43
Total	74,589	100	8,954	100

Panel E: Summary of Stock Characteristics							
	Mean	SD	10%	25%	50%	75%	90%
Market Cap. (millions)	4,245	16,772	103	211	642	2,353	7,855
Price	28.834	56.652	4.147	8.493	17.695	34.524	58.779
Book-to-Market	0.581	0.736	0.113	0.251	0.482	0.783	1.144
CAPM Beta	1.100	0.512	0.486	0.805	1.116	1.404	1.694
Idio. Skewness	0.544	1.098	-0.345	0.045	0.388	0.818	1.518
Idio. Volatility	0.032	0.022	0.014	0.019	0.027	0.038	0.052
Lotteriness	0.215	0.292	0.000	0.000	0.044	0.375	0.701
Illiquidity	0.327	3.295	0.001	0.002	0.007	0.029	0.148

Table 1: Summary of CAPS Data and Variables. This table reports summary statistics of the CAPS data and the characteristics of the stocks underlying our analysis. Panel A summarizes the activity on CAPS. Panel B provides information on the share of optimistic predictions in the sample. Panel C summarizes the frequency and optimism of predictions across expectation horizons for the full CAPS data and the belief-update sample (i.e., predictions terminated and then re-initiated within five days). Panel D shows the number of forecasters with different levels of self-declared investment experience. Panel E summarizes the characteristics of the stocks in the CAPS sample as of the time of a prediction. Table A1 describes the construction of these stock characteristics.

Panel D of Table 1 shows the fraction of the individual forecasters that self-identify on CAPS as having a given level of investment experience. We see that most forecasters do not declare their investment experience. Amongst those who declare their experience level, 56% claim to have medium to high investment experience. We obtain similar numbers in the belief-update sample. Overall, Panels A - D show that the features of the forecasts and the individuals making these forecasts are similar in the full CAPS sample and the belief-update sample.

Finally, Panel E summarizes the characteristics of the stocks that received forecasts in the CAPS sample. The stocks in our sample are small compared to those in the entire CRSP universe. For instance, the median market capitalization of the stocks in our sample is roughly $642 million, close to the average market capitalization of stocks in the bottom 40% of the CRSP universe ($611 million). On the other hand, the sample also features a sizable number of large-cap stocks since about 10% of our sample has a market capitalization that is observed in the 8^{th} decile of the distribution of common stocks in CRSP ($7.593 billion). Firms in our sample are neither disproportionately growth firms nor value firms since the median book-to-market ratio is 0.5, the same as the value observed in the 3^{rd} quintile of the CRSP universe over the same sample period.[15] Finally, there is also a fairly large dispersion in stock characteristics such as CAPM beta, idiosyncratic volatility, idiosyncratic skewness, and illiquidity. It is this heterogeneity in stock characteristics that allows us to conduct further tests on the mechanism later in the paper.

2.2 Measuring News About a Stock

Since we are interested in studying how forecasters respond to incoming information, it is important to measure such information. We do not observe the exposure to information directly. However, we argue that a stock's recent return represents a natural information proxy for the forecasters on CAPS. This is for four reasons. First, as seen in Figure 1, CAPS reports stock returns on its prediction page, making this piece of information very salient to individuals initiating forecasts on the platform. Second, CAPS incentivizes forecasters to pay attention to

[15] We draw these comparisons using data on stock characteristics from Ken French's website for the 2006-2020 sample period.

stocks' recent performance. This is because forecasters' performance ranking is updated daily based on stocks' returns relative to the market. Therefore, to the extent that forecasters care about their rating on the platform, they are likely to pay attention to this simple return metric. Third, although it is unclear whether recent stock returns represent a predictor of future stock performance that a CAPS forecaster should objectively care about it, all we need for our study is that the recent return of a stock affects forecasters' subjective beliefs. Past work indicates that due to the widespread presence of extrapolation in financial markets (e.g., Greenwood and Shleifer, 2014; Barberis et al., 2015; Cassella and Gulen, 2018) and in social finance forums (e.g., Dim, 2020; Da et al., 2021), CAPS forecasters are likely to interpret, on average, good past returns as a signal of good future stock performance, and to interpret poor recent stock returns as a negative signal of the future performance of a stock. Fourth, other measures of news, such as earnings announcements, exist, but they are infrequent and would limit the scope of our analysis to a much smaller sample. In contrast, returns are readily available.[16]

All in all, our primary measure of news is computed as the return of a stock relative to the SPY ETF, because this is the exact index benchmark that CAPS uses to evaluate individuals' prediction accuracy. We also conduct robustness tests using stock returns in excess of the S&P 500 ˆGSPC index, which is the standard market proxy in the literature, and raw individual stock returns. Following recent work on extrapolation in the cross-section in Da et al. (2021), we focus on weekly returns. More so, in keeping with their evidence, we also construct return-based news metrics based on an exponentially weighted average return of past 12 non-overlapping weekly returns, i.e., three months' worth of past return realizations.[17]

Table 2 summarizes these return-based news measures computed as of $t-1$ before prediction initiation on day t. Panel A (Panel B) summarizes the distribution of the returns leading up to optimistic (pessimistic) predictions, i.e., predictions that the stock will outperform (underperform) the market. The properties of the returns are measured for both the full sample of CAPS predictions and the belief-update events, respectively. These summary statistics provide

[16]While returns have many useful properties within the context of our empirical setup, later in Section 4.2 we repeat the analysis focusing on earnings surprises as the relevant news metric, and find similar results.

[17]The weight for a given prior week $s \in [1, 2, ..., 12]$ return is given by $w_s = \frac{\lambda^{s-1}}{\sum_{j=1}^{12} \lambda^{j-1}}$, where we set the parameter $\lambda = 0.59$ based on the estimates in Da et al. (2021).

a first indication that, consistent with the literature, beliefs on CAPS respond to recent stock returns: the average return leading up to an optimistic prediction is positive, and the average return leading up to a pessimistic prediction is negative.

	CAPS Sample				Belief-update Sample			
	Obs.	Mean	SD	Median	Obs.	Mean	SD	Median
Panel A: Optimistic predictions								
Ret - SPY	2,518,339	0.0048	0.0606	0.0023	79,709	0.0074	0.0744	0.0089
Ret - GSPC	2,518,339	0.0052	0.0606	0.0027	79,709	0.0078	0.0743	0.0094
Ret	2,518,339	0.0056	0.0687	0.0050	79,709	0.0044	0.0848	0.0072
Weighted Ret - SPY	2,492,646	0.0034	0.0321	0.0023	78,130	0.0050	0.0418	0.0073
Weighted Ret - GSPC	2,492,646	0.0038	0.0321	0.0026	78,130	0.0054	0.0418	0.0077
Weighted Ret	2,492,646	0.0045	0.0359	0.0049	78,130	0.0031	0.0472	0.0062
Panel B: Pessimistic predictions								
Ret - SPY	563,706	-0.0041	0.0749	-0.0075	52,790	-0.0482	0.0819	-0.0489
Ret - GSPC	563,706	-0.0037	0.0749	-0.0072	52,790	-0.0478	0.0818	-0.0486
Ret	563,706	-0.0043	0.0835	-0.0062	52,790	-0.0502	0.0909	-0.0499
Weighted Ret - SPY	552,871	-0.0010	0.0404	-0.0031	51,263	-0.0274	0.0472	-0.0305
Weighted Ret - GSPC	552,871	-0.0006	0.0404	-0.0027	51,263	-0.0269	0.0472	-0.0301
Weighted Ret	552,871	-0.0005	0.0445	-0.0012	51,263	-0.0278	0.0516	-0.0300

Table 2: Stock-Return News Before Prediction Initiations on CAPS. This table reports the distribution of the stock return-based news measures computed as of $t-1$ before prediction initiations on day t in the full CAPS sample and belief-update sample, respectively. The returns are winsorized at the top and bottom 5 percentiles to reduce the influence of outliers. Panel A summarizes the returns leading up to optimistic predictions. Panel B summarizes those leading up to pessimistic predictions. Ret is the stock's one-week (five trading days) return. Ret $-$ SPY is the stock's one-week return minus that of the SPY ETF. Ret $-$ GSPC is the stock's one-week return minus that of the S&P 500 ˆGSPC index. "Weighted Ret" is constructed based on the extrapolation framework of Da et al. (2021) as described in Footnote 17. "WeightedRet $-$ SPY" and "WeightedRet $-$ GSPC" are computed in a similar way using Ret $-$ SPY and Ret $-$ GSPC, respectively.

To conduct a more formal validation of these news measures, we regress an indicator variable for future optimistic forecasts on day t on different negative news indicators computed as of $t-1$. The negative news indicator equals one when one of the measures described above is negative (e.g., when a stock underperforms the market). The results summarized in Table 3 indicate that across the different specifications and negative news measures, negative news realizations for a stock significantly predict a lower likelihood of optimistic predictions for that stock. For instance, in Panel A, column (1), negative news predicts a decline in the likelihood of optimistic predictions by 4.5 percentage points depending on the specification, corresponding to a 5.5 percent decline in the probability of optimism relative to the unconditional mean. The magnitude of this effect is similar across panels. Moreover, this result survives the inclusion of several sets of fixed effects, stock-level and forecaster-specific control variables.

We use the same regression setup to validate further the informativeness of the negative news indicators in the belief-update sample, which is the focus of our subsequent analysis.

	Future Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Negative News (Ret − SPY)	-0.045***	-0.029***	-0.029***	-0.023***	-0.024***	-0.018***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Observations	3,082,045	3,080,616	3,080,493	3,080,395	2,883,826	2,776,250
Adj. R^2	0.003	0.252	0.259	0.363	0.376	0.432
Panel B						
Negative News (Ret − GSPC)	-0.046***	-0.030***	-0.029***	-0.023***	-0.025***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Observations	3,082,045	3,080,616	3,080,493	3,080,395	2,883,826	2,776,250
Adj. R^2	0.004	0.252	0.259	0.363	0.376	0.432
Panel C						
Negative News (Ret)	-0.048***	-0.029***	-0.032***	-0.024***	-0.026***	-0.018***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Observations	3,082,045	3,080,616	3,080,493	3,080,395	2,883,826	2,776,250
Adj. R^2	0.004	0.252	0.259	0.363	0.375	0.432
Panel D						
Negative News (Weighted Ret − SPY)	-0.046***	-0.028***	-0.027***	-0.022***	-0.023***	-0.019***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)
Observations	3,045,517	3,044,068	3,043,944	3,043,843	2,883,736	2,776,157
Adj. R^2	0.004	0.252	0.258	0.361	0.375	0.432
Panel E						
Negative News (Weighted Ret − GSPC)	-0.047***	-0.029***	-0.028***	-0.022***	-0.023***	-0.019***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)
Observations	3,045,517	3,044,068	3,043,944	3,043,843	2,883,736	2,776,157
Adj. R^2	0.004	0.252	0.258	0.361	0.375	0.432
Panel F						
Negative News (Weighted Ret)	-0.052***	-0.028***	-0.032***	-0.023***	-0.024***	-0.017***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Observations	3,045,517	3,044,068	3,043,944	3,043,843	2,883,736	2,776,157
Adj. R^2	0.004	0.252	0.258	0.361	0.375	0.432
Controls	No	No	No	No	Yes	Yes
Forecaster FE	No	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	No
Stock FE	No	No	No	Yes	Yes	No
Stock x Month FE	No	No	No	No	No	Yes

Table 3: Predictive Power of Negative News for Future Beliefs. This table shows the results of regressing a dummy variable for optimism on different negative news indicator variables in the full CAPS sample. The optimism dummy variable equals one for predictions that a stock will outperform the market and zero otherwise. The negative news indicator— measured as of $t-1$ for a prediction on day t— equals one if the stock return measure denoted in parenthesis in the table is negative and zero otherwise. The construction of these underlying stock returns is described under Table 2. Where indicated, the control variables included in the regression are the log of market capitalization, log book-to-market ratio, CAPM Beta, stock consensus optimism on CAPS, log of the number of the forecaster's outstanding predictions, and the average optimism on the forecaster's outstanding predictions. Further details about these control variables are in Table A1. Standard errors in parentheses are clustered at the forecaster and day levels.

The results, reported in the odd-numbered columns of Table 4, confirm that recent returns predict future beliefs in the sample of belief revisions that we study.[18] In fact, the predictive power of returns for future beliefs grows in the belief-update sample relative to the full sample. This is expected because the belief-update sample concerns forecasters who already have an outstanding prediction on a given stock and are, therefore, more likely to pay attention to the stock and its returns. More importantly, the stronger predictive power of past returns for future beliefs observed in the belief-update sample gives us confidence that our return-based measures can be useful in studying how beliefs respond to incoming news.

3 Optimism Shifting Evidence

The evidence above indicates that, on average, forecasters respond to news about a stock, in that the likelihood of holding optimistic beliefs about a stock declines following negative news. While strong unconditionally, this result may greatly differ conditional on a forecaster's existing beliefs when negative news is observed. In particular, a large body of theoretical work argues that forecasters can selectively acquire or distort incoming information to preserve existing beliefs.[19] Recent work by Cookson et al. (2023) shows evidence that bullish forecasters are more likely to follow other forecasters who are also bullish about the same stock due to the strategic avoidance of incoming negative news and under-reaction to the news relative to forecasters who were not previously bullish.

The first step of our analysis in this section is to complement this recent evidence by investigating whether negative news shapes beliefs differently, conditional on a forecaster's expectation before the arrival of the news. We focus on belief-update events, i.e., events in which, following news about a stock, a forecaster ends an existing prediction for that stock on day t and begins a new prediction on the same stock within five days. We estimate the following

[18] For brevity, we report the results based on the exponentially weighted returns, which are qualitatively similar, in Table A5 of the Appendix.

[19] See Gentzkow and Shapiro (2010), Golman et al. (2017) and Andries and Haddad (2020) for recent theoretical work on agents selectively acquiring information that supports their existing or desired beliefs.

	Future Optimisim											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Neg News based on Ret − SPY												
Negative News	-0.154***	-0.167***	-0.146***	-0.162***	-0.125***	-0.154***	-0.130***	-0.135***	-0.113***	-0.129***	-0.064***	-0.089***
	(0.011)	(0.015)	(0.009)	(0.014)	(0.008)	(0.014)	(0.010)	(0.015)	(0.009)	(0.015)	(0.007)	(0.013)
Past Optimism x Negative News		0.106***		0.104***		0.102***		0.081***		0.080***		0.066***
		(0.013)		(0.013)		(0.012)		(0.013)		(0.012)		(0.012)
Past Optimism		0.397***		0.386***		0.334***		0.370***		0.318***		0.201***
		(0.033)		(0.031)		(0.027)		(0.038)		(0.033)		(0.029)
Observations	123,117	123,117	123,055	123,055	122,506	122,506	119,268	119,268	118,706	118,706	84,669	84,669
Adjusted R-squared	0.469	0.579	0.494	0.593	0.535	0.605	0.597	0.667	0.628	0.677	0.696	0.714
Panel B: Neg News based on Ret − GSPC												
Negative News	-0.154***	-0.166***	-0.146***	-0.161***	-0.126***	-0.153***	-0.130***	-0.135***	-0.113***	-0.129***	-0.064***	-0.088***
	(0.011)	(0.015)	(0.009)	(0.014)	(0.008)	(0.014)	(0.010)	(0.015)	(0.009)	(0.014)	(0.007)	(0.013)
Past Optimism x Negative News		0.105***		0.103***		0.100***		0.080***		0.079***		0.063***
		(0.013)		(0.013)		(0.012)		(0.013)		(0.012)		(0.012)
Past Optimism		0.398***		0.387***		0.335***		0.371***		0.319***		0.203***
		(0.032)		(0.031)		(0.027)		(0.038)		(0.033)		(0.029)
Observations	123,117	123,117	123,055	123,055	122,506	122,506	119,268	119,268	118,706	118,706	84,669	84,669
Adjusted R-squared	0.469	0.579	0.494	0.593	0.535	0.605	0.597	0.667	0.628	0.677	0.696	0.714
Panel C: Neg News based on Ret												
Negative News	-0.131***	-0.151***	-0.139***	-0.153***	-0.120***	-0.144***	-0.123***	-0.128***	-0.106***	-0.122***	-0.052***	-0.079***
	(0.011)	(0.014)	(0.009)	(0.013)	(0.008)	(0.013)	(0.010)	(0.014)	(0.008)	(0.014)	(0.007)	(0.013)
Past Optimism x Negative News		0.105***		0.098***		0.095***		0.078***		0.076***		0.064***
		(0.012)		(0.012)		(0.011)		(0.012)		(0.012)		(0.012)
Past Optimism		0.406***		0.395***		0.343***		0.376***		0.325***		0.205***
		(0.032)		(0.030)		(0.027)		(0.038)		(0.033)		(0.029)
Observations	123,117	123,117	123,055	123,055	122,506	122,506	119,268	119,268	118,706	118,706	84,669	84,669
Adj. R^2	0.462	0.577	0.490	0.592	0.532	0.604	0.594	0.666	0.626	0.676	0.695	0.713
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Stock FE	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Forecaster FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Month FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes

Table 4: Conditional Response to Negative News This table shows the results of regressing a dummy variable for optimism on different negative news indicator variables focusing on the belief-update sample. The optimism dummy variable equals one for predictions that a stock will outperform the market and zero otherwise. The negative news indicator— measured as of $t-1$ where t is the past prediction termination day— equals one if the stock return measure denoted in the panel label is negative and zero otherwise. The construction of the underlying stock returns is described under Table 2. Where indicated, the control variables included in the regression are the negative news realized between the past prediction termination and new prediction initiation, log of market capitalization, log book-to-market ratio, CAPM Beta, stock consensus optimism on CAPS, log of the number of the forecaster's outstanding predictions, the average optimism on the forecaster's outstanding predictions, and the ex-market return of the forecaster's portfolio of outstanding predictions. Further details about these control variables are in Table A1. Standard errors in parentheses are clustered at the forecaster and day levels.

regression:

$$Optimism_{i,j,(t,t+5)} = Negative\ News_{i,j,t-1}(\beta_1 + \beta_2 Optimism_{i,j,t-1}) + \Gamma\, \mathbf{X}_{i,j,t} + \alpha_i + \gamma_j + \delta_t + \epsilon_{i,j,(t,t+5)}, \quad (1)$$

where, i, j, and t index individual, stock, and day, respectively. *Negative News*$_{i,j,t-1}$ is defined, like in the previous section, as a dummy that equals one if the stock return, raw or in excess of the market index, is negative in the week (five trading days) ending on day $t-1$.[20] The conditioning variable *Optimism*$_{i,j,t-1}$ is a dummy variable that equals one if forecaster i's outstanding prediction on stock j was optimistic prior to the termination of the prediction on day t. The dependent variable is a dummy variable that equals one (zero) if the forecaster makes an optimistic (pessimistic) prediction about the stock within the next five-day belief update window. Such a window allows for the possible delay that could exist between observing the news, terminating the existing prediction and entering a new prediction on CAPS.

The regression includes several control variables, captured by $\mathbf{X}$, that allow us to account for several other factors that may matter for belief updating. First, there are forecaster-level controls, namely (i) forecaster outstanding optimism about stock j, i.e., *Optimism*$_{i,j,t-1}$, to account for stickiness in beliefs; (ii) forecaster age on CAPS to account for learning and experience effects in belief formation; (iii) forecaster number of outstanding predictions on CAPS, as a proxy for attention; (iv) forecaster time-varying average optimism across outstanding predictions besides stock j, as a proxy for person-specific time-varying optimism towards individual stocks relative to the market; (v) the average value of the return-based news measure across all stocks for which the forecaster has an outstanding prediction, to account for spill-over effects in beliefs across stocks. Second, to account for peer effects, we include CAPS consensus beliefs about the focal stock. Third, to account for the fact that optimism about stocks can differ systematically based on stock characteristics, we control for size, book-to-market, and CAPM beta. Finally, to

[20]Note that, while the negative-news dummy is based on a stock's return and as such is not per se forecaster-specific, we index it by forecaster because the different timing with which forecasters terminate an existing prediction effectively makes the negative-news indicator variable specific to both forecaster and stock.

rule out the concern that perhaps it is the news realized during the belief-update window that drives the new forecast instead of the news that prompted the outstanding prediction's termination, we include a dummy variable for future negative news computed over the five-day window (t,t+5). Table A1 describes the construction of all these control variables.

The main coefficient of interest in Eq. (1) is β_2. The coefficient measures the differential response to negative news that is observed when a forecaster holds optimistic beliefs prior to receiving the news, relative to the case in which his prior belief about that stock is pessimistic. The conjecture that past optimism leads to under-reaction to negative news about a stock equates to a prediction that β_2 is positive: whereas negative news may be associated with lower future optimism on average, such association will be weaker among those who were previously optimistic about a stock. The estimation results are reported in the even-numbered columns of Table 4. We find a positive and sizeable β_2 coefficient estimate across board, indicating that, indeed, optimistic individuals in financial markets tend to react less to negative news. This result is robust to controlling for forecasters' past beliefs about a stock, which indicates that the result does not simply reflect stickiness in beliefs. Moreover, the result survives the inclusion of other control variables described earlier and several fixed effects.[21]

Two broad explanations for this result exist, namely, distorted information acquisition, i.e., the avoidance of negative news, and distorted information processing, i.e., the misinterpretation of incoming information. We argue that distorted information acquisition (Golman et al., 2017; Cookson et al., 2023) is unlikely to be solely responsible for optimists' diminished sensitivity to negative news. This is because information avoidance would likely result in a lack of reaction to incoming news and no belief updating, while our result concerns a sample in which individuals actively engage in belief updating following news. Moreover, strategically avoiding negative news that is as salient as recent stock returns can be excessively costly and ultimately unsuccessful.

[21] Day fixed effects help absorb common shocks to beliefs in the time series. Stock and Stock-month fixed effects help control for unobservable stock characteristics that change at a monthly frequency or lower, and which could predict stock returns and hence impact optimism. Finally, forecaster fixed effects allow us to perform a within-forecaster analysis, whereby we measure how the same forecaster responds to negative news depending on whether he was optimistic about a stock prior to observing the news.

We argue that in our setting, distortion in information processing is a more natural candidate that explains optimists' diminished response to negative news. That such distortions exist in financial markets is particularly likely since, as argued in Rabin and Schrag (1999), misinterpreting information in support of one's existing beliefs is more likely in situations of uncertainty and when the information content of an incoming signal has an ambiguous interpretation. In such a setting, individuals in the lab have been shown to selectively interpret incoming information as supportive of their existing beliefs (Lord et al., 1979; Darley and Gross, 1983), and such a tendency has been shown to affect experimental subjects' assessment of the predictive power of signals received at present for future events (Nisbett and Ross, 1980).

In the context of belief updating about stocks' performance following negative news, the existing theoretical and experimental work above suggests that optimists may be able to maintain their pre-existing optimism by selectively interpreting incoming negative news as supportive of their initial optimism. In particular, we conjecture that these optimistic forecasters react to recent negative news as if such news has a more clear-cut negative impact on the performance of a stock in the short run, while it is far more uncertain what the news implies for the performance of a stock on a longer horizon. Hence, we hypothesize that when optimists react to negative news, they are able to maintain their pre-existing optimism by selectively interpreting the incoming negative news as relevant for the short run but not the long run. This distorted information processing mechanism is what we term *optimism shifting*.

The data on CAPS presents a unique opportunity to test for optimism shifting. This is because forecasters engaging in belief updating on the platform have to not only enter a new prediction but also specify a prediction horizon. Therefore, we can test for optimism shifting by asking whether optimists' diminished sensitivity to negative news is particularly pronounced when optimistic forecasters shift their predictions to a longer horizon. To this end, we define *Longer Horizon*, an indicator variable that equals one if a forecaster who engages in a belief-update event chooses a longer horizon for the new prediction relative to their previous prediction about the stock, and zero otherwise. Our main regression is as follows:

$$
\begin{aligned}
\mathit{Optimism}_{i,j,(t,t+5)} = \beta\, \mathit{Optimism}_{i,j,t-1} \times \mathit{Negative\ News}_{i,j,t-1} \times \mathit{Longer\ Horizon}_{i,j,(t,t+5)} \\
+ \Gamma\, \mathbf{X}_{i,j,t} + \alpha_i + \gamma_j + \delta_t + \epsilon_{i,j,(t,t+5)},
\end{aligned}
\tag{2}
$$

The main coefficient of interest is β. The optimism-shifting hypothesis suggests that β should be positive, i.e., a weaker reaction to negative news is observed among optimists who shift their prediction from a shorter to a longer forecast horizon. In the regression, the set of controls $\mathbf{X}$ includes all single interaction terms and main effects in the regression, alongside the control variables introduced in Eq. (1).[22]

Table 5 reports the estimates of Eq. (2). The results provide strong support for our optimism-shifting hypothesis. The β coefficient estimate is economically large, ranging from 7.1% to 9.1% across different estimations. These estimates imply that optimists' documented under-response to negative news grows by roughly 100% for those who engage in optimism shifting relative to those who do not. For instance, in column (1) of Table 5, the baseline coefficient on the interaction term for Past Optimism and Negative News is 0.079, while the overall effect in the presence of longer horizon shifts is 0.079 + 0.083. The result is robust to the inclusion of several controls, sets of fixed effects and the use of alternative negative news proxies.

4 Robustness

4.1 Simultaneity

The estimates in Table 5 are obtained using standard OLS estimation. However, forecasters on CAPS simultaneously choose a prediction direction (the dependent variable) and a prediction horizon (an input to one of the regressors). Since the prediction horizon affects the construc-

[22] To complement our main empirical approach, we also estimated a regression of future forecast horizon change on the interaction of past forecaster's optimism and a negative-news dummy. This result, available upon request, shows that optimistic forecasters indeed increase their forecast horizon following negative news. That said, such a specification does not allow us to answer our research question precisely. This is because this test does not reveal the likelihood that a prior optimist stays optimistic following negative, upon choosing a longer forecast horizon.

	Future Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Longer Horizon	0.083***	0.078***	0.071***	0.091***	0.083***	0.091***
	(0.025)	(0.024)	(0.023)	(0.025)	(0.024)	(0.028)
Past Optimism x Negative News	0.079***	0.078***	0.077***	0.064***	0.065***	0.052***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.012)
Negative News	-0.139***	-0.135***	-0.130***	-0.117***	-0.113***	-0.076***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.013)
Past Optimism	0.467***	0.454***	0.401***	0.422***	0.369***	0.245***
	(0.034)	(0.033)	(0.029)	(0.040)	(0.035)	(0.030)
Longer Horizon	0.315***	0.313***	0.297***	0.304***	0.285***	0.231***
	(0.026)	(0.025)	(0.022)	(0.030)	(0.026)	(0.026)
Past Optimism x Longer Horizon	-0.314***	-0.306***	-0.284***	-0.292***	-0.269***	-0.207***
	(0.030)	(0.029)	(0.025)	(0.034)	(0.030)	(0.028)
Negative News x Longer Horizon	-0.071***	-0.068***	-0.062***	-0.091***	-0.082***	-0.082***
	(0.024)	(0.023)	(0.022)	(0.024)	(0.023)	(0.025)
Ftr. Negative News	-0.007**	-0.006**	-0.005**	-0.004	-0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Log(Number of Picks)	0.001	0.004	0.002	0.003	0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Portfolio Optimism	0.304***	0.316***	0.324***	0.227***	0.235***	0.240***
	(0.026)	(0.023)	(0.020)	(0.030)	(0.028)	(0.027)
Portfolio Ex-market Ret.	-0.026	0.004	0.001	-0.009	-0.014	0.050
	(0.075)	(0.073)	(0.073)	(0.066)	(0.065)	(0.074)
CAPS Consensus	0.295***	0.297***	0.236***	0.272***	0.222***	
	(0.024)	(0.022)	(0.025)	(0.021)	(0.025)	
Log(Market Cap.)	0.003***	0.004***	0.021***	0.007***	0.021***	
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	
Log(Book-to-Market)	-0.001*	-0.002***	-0.000	-0.002***	-0.000	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
CAPM Beta	-0.009***	-0.005**	0.003	-0.005**	0.001	
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
Log(CAPS Age)	-0.002	-0.002	-0.002			
	(0.001)	(0.002)	(0.001)			
Day FE	No	Yes	Yes	Yes	Yes	No
Stock FE	No	No	Yes	No	Yes	No
Forecaster FE	No	No	No	Yes	Yes	Yes
Stock x Month FE	No	No	No	No	No	Yes
Observations	123,117	123,055	122,506	119,268	118,706	84,669
Adj. R^2	0.590	0.604	0.615	0.674	0.683	0.718

Table 5: Optimism Shifting. This table shows the results of estimating Eq. (2). The sample consists of individuals who ended their existing prediction on stock j as of day t and started a new prediction on the same stock within the next five days. *Future Optimism* (*Past Optimism*) is an indicator variable that equals one if investors' future (past) prediction is that stock j will outperform the S&P 500 index and zero otherwise. *Negative News* is an indicator variable that equals one if stock j's past one-week stock return in excess of the SPY index return ending $t-1$ is negative, and zero otherwise. *Longer Horizon* is an indicator variable that equals one if the horizon of Future Optimism is longer than that of Past Optimism. The prediction horizons are described in Section 2.1. Further details about the control variables are in Table A1. Standard errors are clustered at the forecaster and day levels.

tion of the *Longer Horizon* regressor, the OLS estimation of Table 5 could potentially lead to biased coefficient estimates due to a simultaneity problem. Hence, it is important to address the simultaneity concern before one can confidently interpret the results.

To this end, we adopt an instrumental-variable (IV) approach. Specifically, we follow recent work in economics and finance that uses lagged values of a regressor as an instrument (e.g., Reed, 2015; Bøler et al., 2015; Doraszelski et al., 2018). In our context, we use the forecast horizon of the previous prediction, $Horizon_{i,j,t-1}$, as an instrument for the *Longer Horizon* dummy variable.

We expect the instrument to be strong. This is because CAPS only allows for a finite set of prediction horizons. So, in the cross-section of forecasters and predictions, a higher value of $Horizon_{i,j,t-1}$ implies that a smaller set of possible prediction horizons is available to those who want to shift the horizon of their existing optimism to a longer horizon. With respect to the exogeneity assumption underlying the validity of the IV procedure, we note that our lagged-horizon instrument could, in principle, influence future beliefs, not just by influencing future horizon choice. For instance, it is possible that the choice of lagged horizon may have influenced the choice of lagged beliefs, and these lagged beliefs could, in turn, influence future beliefs. However, our first-stage regressions explicitly control for lagged beliefs, as well as the full set of control variables that we include in the second stage. This helps make the case for the only-through condition linking past horizon choice to future beliefs via future horizon choice.

Our IV estimation comprises the following first-stage and second-stage regressions:

$$1^{st}: \begin{cases} LH_{i,j,(t,t+5)} \cdot NN_{i,j,t-1} \cdot O_{i,j,t-1} & = a_1 + [b_{1,0} + b_{1,1}O_{i,j,t-1} + (b_{1,2} + b_{1,3}O_{i,j,t-1}) \cdot NN_{i,j,t-1}] \cdot H_{i,j,t-1} + \Gamma_1 \mathbf{C}_{i,j,t} + u_1 \\ LH_{i,j,(t,t+5)} \cdot NN_{i,j,t-1} & = a_2 + [b_{2,0} + b_{2,1}O_{i,j,t-1} + (b_{2,2} + b_{2,3}O_{i,j,t-1}) \cdot NN_{i,j,t-1}] \cdot H_{i,j,t-1} + \Gamma_2 \mathbf{C}_{i,j,t} + u_2 \\ LH_{i,j,(t,t+5)} \cdot O_{i,j,t-1} & = a_3 + [b_{3,0} + b_{3,1}O_{i,j,t-1} + (b_{3,2} + b_{3,3}O_{i,j,t-1}) \cdot NN_{i,j,t-1}] \cdot H_{i,j,t-1} + \Gamma_3 \mathbf{C}_{i,j,t} + u_3 \\ LH_{i,j,(t,t+5)} & = a_4 + [b_{4,0} + b_{4,1}O_{i,j,t-1} + (b_{4,2} + b_{4,3}O_{i,j,t-1}) \cdot NN_{i,j,t-1}] \cdot H_{i,j,t-1} + \Gamma_4 \mathbf{C}_{i,j,t} + u_4 \end{cases}$$

$$2^{nd}: \quad O_{i,j,(t,t+5)} = \beta\, \hat{O}_{i,j,t-1} \cdot \hat{NN}_{i,j,t-1} \cdot \hat{LH}_{i,j,(t,t+5)} + \Gamma\, \mathbf{X}_{i,j,t} + \alpha_i + \gamma_j + \delta_t + \epsilon_{i,j,(t,t+5)},$$

where, due to space constraint, *Longer Horizon*, *Optimisim*, and *Negative News*, previously defined, are abbreviated as *LH*, *O*, and *NN*, respectively, and the principal instrument, lagged-horizon, is abbreviated as H. In the first-stage equations, *Longer Horizon* is instrumented by lagged-horizon, while the interaction of a variable with *Longer Horizon* is instrumented by the variable's interaction with lagged-horizon. **C** captures the other control variables used in Eq. (2) and allows us control for potential confounding factors. In the second-stage equation, we use the predicted values, denoted with a hat above them, from the first-stage regressions. Vector $\mathbf{X}$ includes all single and two-way interaction terms, as well as the other controls in our OLS estimation.

While the full estimates of the first-stage regressions are reported for brevity in Table A2 of the Appendix, we report standard first-stage diagnostics in Table 6. These diagnostics strongly indicate that the first stage does not suffer from the weak-instrument problem. For this reason, we feel compelled to estimate the second stage, whose results are equally reported in Table 6. Across board, when we use the instrumented *Longer Horizon* dummy in our tests of optimism shifting, we find even stronger evidence of optimism shifting.

	Future Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Longer Horizon	0.205***	0.171***	0.151***	0.213***	0.192***	0.185***
	(0.067)	(0.062)	(0.058)	(0.072)	(0.066)	(0.066)
Past Optimism x Negative News	0.054***	0.056***	0.057***	0.043***	0.045***	0.038***
	(0.016)	(0.015)	(0.014)	(0.015)	(0.014)	(0.011)
Negative News (NN)	-0.103***	-0.102***	-0.099***	-0.087***	-0.085***	-0.053***
	(0.019)	(0.017)	(0.016)	(0.017)	(0.016)	(0.011)
Past Optimism (PO)	0.555***	0.546***	0.490***	0.512***	0.453***	0.323***
	(0.038)	(0.036)	(0.031)	(0.045)	(0.038)	(0.028)
Longer Horizon (LH)	0.584***	0.592***	0.559***	0.636***	0.590***	0.479***
	(0.088)	(0.084)	(0.076)	(0.116)	(0.102)	(0.078)
Past Optimism x Longer Horizon	-0.900***	-0.888***	-0.830***	-0.918***	-0.844***	-0.719***
	(0.117)	(0.111)	(0.100)	(0.154)	(0.134)	(0.105)
Negative News x Longer Horizon	-0.216***	-0.191***	-0.181***	-0.250***	-0.235***	-0.237***
	(0.077)	(0.070)	(0.067)	(0.085)	(0.080)	(0.070)
Ftr. Negative News	-0.006**	-0.005**	-0.005*	-0.004	-0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(Number of Picks)	-0.003	-0.000	-0.002	0.002	0.001	-0.005
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Portfolio Optimism	0.279***	0.286***	0.299***	0.203***	0.213***	0.223***
	(0.025)	(0.022)	(0.019)	(0.031)	(0.028)	(0.026)
Portfolio Ex-market Ret.	-0.055	-0.006	-0.011	-0.001	-0.005	0.060
	(0.077)	(0.076)	(0.076)	(0.070)	(0.070)	(0.078)
CAPS Consensus	0.281***	0.281***	0.227***	0.260***	0.214***	
	(0.022)	(0.021)	(0.024)	(0.020)	(0.024)	
Log(Market Cap.)	0.002**	0.003***	0.017***	0.006***	0.017***	
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	
Log(Book-to-Market)	-0.001	-0.001**	-0.000	-0.001***	-0.000	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
CAPM Beta	-0.011***	-0.007***	0.002	-0.006***	0.000	
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
Log(CAPS Age)	-0.004***	-0.002	-0.002			
	(0.001)	(0.001)	(0.001)			
Day FE	No	Yes	Yes	Yes	Yes	No
Stock FE	No	No	Yes	No	Yes	No
Forecaster FE	No	No	No	Yes	Yes	Yes
Stock x Month FE	No	No	No	No	No	Yes
Observations	123,117	123,055	122,506	119,268	118,706	84,669
Adj. R^2	0.558	0.509	0.278	0.290	0.122	-0.356
First stage F-stat (LH)	81.4	91.7	112.2	206.4	246.5	351.9
First stage F-stat (LH x NN)	121.4	111.4	98.4	178.8	207.4	268.1
First stage F-stat (LH x PO)	145.8	161.5	157.2	170.3	193.8	219.7
First stage F-stat (LH x NN x PO)	109.0	129.8	118.2	132.4	147.3	149.2

Table 6: Optimism Shifting – IV Estimation. This table shows the results of estimating Eq. (2) using two-stage least squares, with the past prediction horizon (in years) serving as the primary instrument for the Longer Horizon dummy variable. Accordingly, the interaction of the longer horizon dummy and a predetermined variable is instrumented by the interaction of the primary instrument and the predetermined variable. The first-stage estimates are reported in the Appendix, Table A2. The sample and all variables are as described under Table 5. Standard errors are clustered at the forecaster and day levels.

4.2 Alternative News-metrics

Our main news metric is return-based. We select it by noting that the return of a stock relative to the market is the most likely piece of information agents in our sample pay attention to, given the CAPS interface and ranking system. In this section, we conduct robustness tests using alternative news measures, all painting a consistent picture.

First, we construct two alternative return-based negative news measures over the same one-week window ending $t-1$ as our primary news measure, Ret − SPY. The first measure is based on whether the one-week stock return in excess of the non-tradable S&P 500 ˆGSPC index (Ret − GSPC) is negative. The second is based on whether the raw one-week stock return (Ret) is negative. We already saw from Table 4 that these news measures yield similar inferences for the forecaster's conditional response to news. Next, we re-estimate Eq. (2) using these alternative news measures and report the results in Tables A3 and A4, respectively. The results are strikingly similar to the estimates in the main result, Table 5.

Second, we build on the earlier literature that documents that older returns beyond the most recent week also influence people's expectations of future stock returns, although with declining weights. We construct news measures equivalent to Ret − SPY, Ret − SPY, and Ret, with the only exception being that they rely on exponentially-weighted weekly returns over the past three-month period ending $t-1$ as described in Footnote 17. We then re-do the analysis of Eqs. (1) and (2) using these alternative news measures. The results summarized in Tables A5 and A6, respectively, again paint a consistent picture. Optimists under-respond to negative news and tend to shift their optimism to a longer horizon following negative news.

Finally, we step away from the return-based news measures and instead construct the negative news indicator based on firms' earnings announcements. Earnings announcements are regarded as major news events that many market participants pay attention to. We define stock j to have released negative news as of day t if there was a negative earnings surprise over the preceding 30-day window ending $t-1$ due to the infrequent nature of earnings announcements. Earnings surprise is quantified as the Standardized Unexpected Earnings (SUE), i.e., the difference between a firm's quarterly earnings per share (EPS) and analyst consensus EPS forecast, then normalized by the previous quarter's stock price (Affleck-Graves and Mendenhall, 1992; Livnat and Mendenhall, 2006). We then re-estimate Eq. (2) in a belief-update sample that mimics one of our earlier tests but is focused on belief updates on the heels of earnings announcements. The results are in column (4) of Table A6, again confirming optimism shifting following negative news.

4.3 Alternative Measure of Horizon Shifts

Next, we verify that our results are robust to alternative measures of forecasters' horizon shifts. We consider two alternatives. First, we construct a continuous variable, *Horizon Change (Years)*, as the difference in years between the old prediction horizon and the new one. Specifically, we translate the categorical variables for horizons into years (e.g., three months = 0.25 years), then take the difference between the new and past prediction horizons. Second, we also construct an alternative horizon change measure, denoted *Horizon Change (Rank)*, by first ranking the horizons from 1 (three weeks) to 5 (five years) and then taking the difference between the new and past prediction horizons' ranks. We then re-estimate Eq. (2) using *Horizon Change (Years)* and *Horizon Change (Rank)*, respectively, and summarize the results in Table A7. The results remain unchanged and provide further support for optimism shifting.

4.4 Alternative Definitions of Belief-update Events

Our main analysis uses belief-update events defined as cases where a forecaster ends an outstanding prediction on a stock on day t and initiates a new prediction on the same stock on day $t+\tau$ for $0 \leq \tau \leq 5$ days. One may wonder whether the news that arrives in the interval $(t, t+\tau)$ drives the results instead of the news observed at $t-1$. It is important to assess whether this is the case since the evidence of short-term reversal and liquidity effects at the daily or weekly frequency (e.g., Lehmann 1990; Pástor and Stambaugh 2003) suggests that the return observed in the week leading to time $t-1$ and the return observed in the following week, may be correlated. In light of this concern, we explicitly control in all of our regressions for the returns observed over the belief-update window. As shown above, our results survive this control.

We also investigate whether our results survive other definitions of the time interval τ used to identify belief-update events. We consider two alternative belief-update window definitions:

a shorter one $0 \leq \tau \leq 3$ days and a longer one $0 \leq \tau \leq 10$ days. Table A9 summarizes the estimation results of Eq. (2) for both alternative belief-update windows, respectively. The results are consistent with the evidence of optimism-shifting presented above.

4.5 External Validity

One may wonder whether the optimism-shifting evidence manifests in other settings beyond CAPS or is simply driven by the specific features of CAPS. To investigate whether this is the case, we need another source of data that will allow us to measure changes expectation horizon in the context of financial investments. Traditional sources of data used to study beliefs over the term structure, such as the Survey of Professional Forecasters, may not be well suited to study optimism shifting in financial markets and in the cross-section of stocks: the SPF concerns macroeconomic outcomes, rather than the performance of stocks. Rather, to establish external validity, we test for optimism shifting with data from an alternative, well-established social finance forum, Seeking Alpha (SA).[23] While anyone can express their views on stocks' future return performance on the SA platform, SA's environment is not as well-suited as CAPS for testing the optimism-shifting hypothesis. This is because the views expressed on SA have no clear expectation horizon, and there is no notion of prior forecast termination. On the other hand, forecasters' views expressed on the platform are detailed in long-form articles. The richness of the data in this dimension allows us to conduct an *indirect* assessment of expectation horizons using natural language processing techniques.[24]

We use forecasters' viewpoints posted on SA over the period 2005 - 2021 obtained from Dim (2020). For each post, we have the full text, publication date, author's user ID, stock ticker covered, and the user's bullishness label ("Bullish", "Neutral", or "Bearish") that summarizes the forecaster's expectation about the stock. We construct a lexicon of long-term words and then assign each post a "long-term language score". To construct the lexicon, we follow a similar approach detailed in Li et al. (2021). Put succinctly, we fit word embeddings on our article

[23]See, `https://about.seekingalpha.com/`.

[24]Using Seeking Alpha as part of our analysis also has additional benefits. First, SA is a prominent investment social media used by about 20 million unique investors per month for investment ideas. Second, research has shown that interactions on SA are non-redundant and embody cash flow-relevant information (Chen et al., 2014; Dim, 2020; Farrell et al., 2021).

corpus and then find the top 100 or 200 terms closest (i.e., have the highest cosine similarity scores) to our two seed words—"long-term" and "long-haul"—that reflect long-term thinking in terms of their usage context. Finally, we use the lexicon to obtain a long-term language score for each post.[25]

Next, we construct variables similar to those used in our analysis of CAPS. We classify user i's post about stock k on day t as an update to her previous post on $t-h$ about the same stock if the gap between $t-h$ and t is at least ten calendar days and at most one calendar year (or up to three years, for robustness).[26] We define a *Higher Horizon Language* dummy variable that equals one if a user's post about stock k on day t has a higher long-term language score than their previous post on $t-h$ about the same stock and zero otherwise. We define the *Future Optimism* (*Past Optimism*) indicator variable that equals one if the post about stock k on day t ($t-h$) is "Bullish", and zero otherwise. Finally, we define the return-based *Negative News* dummy variable that equals one if stock k's one-week return ending $t-2$ for a post on day t is negative and zero otherwise.[27]

As in our main analysis, we regress *Future Optimism* on the triple interaction term of *Past Optimism* $\times$ *Negative News* $\times$ *Higher Horizon Language*, including similar controls, main effects, and fixed effects as before. Table A10 summarizes the estimation results. Odd-numbered columns are estimated with the two-way interaction term *Past Optimism* $\times$ *Negative News*, and even-numbered columns use the triple interaction term. Panel A (B) focuses on the case where articles' long-term language scores are based on 200 (100) lexicon terms, and there is, at most, a one-year gap between users' prior and new posts. Panels C and D follow a similar pattern but allow for a longer update window of at most three years.

Across the different panels in Table A10, we observe a striking consistency with our earlier evidence based on CAPS. For brevity, we focus on the results obtained in the most conserva-

[25]More formally, the score is the term frequency–inverse document frequency weighted count of long-term lexicon terms that appear in a post, normalized by the total number of words.

[26]We require at least ten calendar days to ensure no overlap between the previous post's publication date and the horizon over which our return-based news measure is computed. The returns are computed over one week, and SA posts take between one and two days to appear on the forum after users' submission to the platform moderators.

[27]We stop at $t-2$ to allow enough time for users to write the long-form article and post it on SA. The results are also not materially different if we define negative news based on returns in excess of the market. We, however, use raw returns in this part of the analysis because, unlike the CAPS forecasters, SA users are not necessarily benchmarking their views against the market index.

tive estimation. In Panel A, column (9) shows a significant coefficient estimate of -0.032 for *Negative News* and 0.019 for *Past Optimism* $\times$ *Negative News*, confirming that optimists under-respond to negative news relative to pessimists. Crucially, column (10) shows a significant coefficient of 0.035 for *Past Optimism* $\times$ *Negative News* $\times$ *Higher Horizon Language*, indicating that optimists' under-response to negative news markedly intensifies when these optimistic forecasters increase the horizon of their prediction, as implied by a higher long-term thinking score.[28] Overall, the analysis provides strong external validation of our optimism-shifting evidence, indicating that optimism-shifting is a robust pattern that manifests in different domains where people update their investment beliefs.

5 Mechanism

In this section, we investigate the mechanisms that underlie optimism shifting. Insofar as optimism shifting is a mechanism that enables individuals to preserve their existing optimism, theories of belief-based utility and motivated beliefs (e.g., Bénabou 2015; Bénabou and Tirole 2016; Caplin and Leahy 2019) offer a relevant conceptual framework. In these theories, individuals choose their beliefs about the future to maximize their overall utility. Central to belief updating in these theories is the idea that beliefs respond to stakes (e.g., Bénabou 2015, Bénabou and Tirole 2016), i.e., a forecaster wishes to remain optimistic about an outcome to the extent that their well-being (financial and otherwise) is exposed to that outcome. We consider three distinct forms of stakes: stock ownership (a financial-stake channel), knowledge (an intangible-stake channel), and self-image (a self-confidence channel).

5.1 Financial Stakes

The first channel we investigate in relation to optimism shifting concerns stock ownership. The idea behind it is straightforward. When an agent owns an asset, some of the agent's future consumption is attached to the future value of the asset. If the agent's utility features an an-

[28] The magnitude of the result in this setting is lower than that of Table 5 (0.037 vs. 0.083 for the triple interaction term). This is not surprising since SA does not offer a direct horizon measure, and, thus, we measure the shifting of beliefs to a longer horizon with noise. On the other hand, the choice of extending the forecasting horizon generates a very large increase in the likelihood that optimistic forecasters remain optimistic following negative news.

ticipatory component, the agent chooses to be optimistic about the asset. This is because such optimism helps the agent hold optimistic beliefs about his own future consumption. In the event the agent receives negative news about the asset, the agent's future consumption can be affected negatively. Due to the anticipatory component of the agent's utility and the financial stake in the asset, the agent chooses to maintain optimistic beliefs about the asset (and hence his future consumption) by engaging in optimism shifting.

To test the stock-ownership channel of optimism shifting, we rely on established evidence in the literature concerning the portfolio holdings of unsophisticated investors like the CAPS participants. We use this evidence to categorize stocks as having either a high or a low likelihood of being held by the individuals in our sample. Specifically, it has been shown that stocks with low market capitalization, low prices, high idiosyncratic volatility, high idiosyncratic skewness, low liquidity, and with lottery-type payoffs feature prominently in individual investors' portfolios (e.g., Barber and Odean, 2000, 2001; Mitton and Vorkink, 2007; Goetzmann and Kumar, 2008; Kumar, 2009). Therefore, to the extent that optimism shifting is linked to belief-based utility via a financial-stakes channel, we expect optimism shifting to be more pronounced among these stocks relative to stocks that do not feature these characteristics.

Incidentally, even if stock ownership did not change across the aforementioned stock characteristics, theory on motivated beliefs would still suggest that motivated beliefs can be stronger for certain stock characteristics than others. In particular, to the extent that a stock characteristic correlates with the opaqueness and uncertainty surrounding stocks' future payoffs, such uncertainty can, in and of itself, magnify the distortions in belief formation that are due to motivated beliefs (e.g., Bénabou 2015, Caplin and Leahy 2019). Similarly, Brunnermeier and Parker (2005) indicate that motivated beliefs induce optimistic beliefs that are particularly pronounced for assets with more skewed payoffs. Ultimately, both the financial-stakes interpretation and the additional predictions of motivated-beliefs models indicate that one should observe stronger optimism shifting for small, opaque, highly volatile stocks with skewed payoffs.

We partition the belief-update sample into two subsamples based on whether a stock ranks above or below the cross-sectional median for a given characteristic as of the end of the last calendar month prior to day t. We then re-estimate Eq. (2) for the two sub-samples and summarize the results for the different characteristics in Table 7, where for brevity, we suppress all the other control variables and instead focus on optimism shifting. The results support the stock-ownership channel in that optimism shifting is much more pronounced among stocks with high idiosyncratic volatility, high idiosyncratic skewness, low price per share, low market capitalization, and high illiquidity—all indicative of high retail investor ownership. Moreover, as Table 7 shows, the difference in optimism shifting between stocks with a high vs. low likelihood of retail ownership is statistically significant at the 5% level in 14 of the 18 reported tests, and failure to reject the null of no significant differences at the 10% level is observed only once. Overall, these results align well with a stock-ownership channel of optimism shifting.

5.2 Knowledge Stakes

Next, we entertain the notion that non-monetary stakes can also lead to optimism shifting. In particular, we argue that when an individual acquires knowledge about a stock, this knowledge represents a form of intangible capital with a value attached to it. Financial economics has recently started to acknowledge and value the acquisition and processing of raw data into knowledge (Eisfeldt and Papanikolaou, 2014, Crouzet et al., 2022, Veldkamp and Chung, 2019, Veldkamp, 2023). We argue that much like the ownership of a financial stake in the firm, possession of knowledge about a firm leads the forecaster to be exposed to the fate of the stock. If a firm, its business, and its industry prosper, knowledge about the firm can be very valuable to the forecaster in the future since it can inform future financial decisions about the stock or lead to higher utility via other means (e.g., job opportunity or career improvement). However, if the firm or its industry struggles, then the forecaster's expected utility derived from possessing knowledge in that firm or industry is at stake. In such situations, knowledge stakes could create an incentive to protect the value of one's knowledge in the face of negative news affecting the focal firm or its industry, resulting in strategies such as optimism shifting.

To test the knowledge-stakes channel, we perform both a cross-forecaster and cross-asset analysis. In the cross-section of forecasters, some forecasters are more focused on firms in certain industries than others. The more a forecaster is focused on a particular industry, the more the rents he expects to receive from his knowledge are tied to the success of that industry.

	Future Optimism					
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: Size						
Past Optimism x Negative News x Longer Horizon	0.019	0.132***	0.042	0.152***	0.035	0.129**
	(0.024)	(0.046)	(0.026)	(0.051)	(0.026)	(0.051)
Observations	87078	34719	83895	33683	83427	33196
Adj. R^2	0.525	0.725	0.608	0.766	0.616	0.780
p-val High = Low	0.007		0.020		0.041	
p-val High > Low	0.004		0.010		0.020	
Panel B: Price						
Past Optimism x Negative News x Longer Horizon	0.024	0.117***	0.034	0.136***	0.026	0.122***
	(0.026)	(0.033)	(0.029)	(0.036)	(0.029)	(0.035)
Observations	72774	48944	69924	47221	69388	46685
Adj. R^2	0.508	0.669	0.598	0.726	0.607	0.738
p-val High = Low	0.012		0.028		0.043	
p-val High > Low	0.006		0.014		0.022	
Panel C: Idio. Vol.						
Past Optimism x Negative News x Longer Horizon	-0.009	0.096***	0.026	0.111***	-0.002	0.117***
	(0.030)	(0.027)	(0.036)	(0.030)	(0.037)	(0.029)
Observations	52518	68988	50188	66776	49555	66158
Adj. R^2	0.472	0.645	0.585	0.702	0.593	0.713
p-val High = Low	0.009		0.064		0.025	
p-val High > Low	0.004		0.032		0.013	
Panel D: Idio. Skew.						
Past Optimism x Negative News x Longer Horizon	0.029	0.108***	0.060*	0.111***	0.048	0.107***
	(0.027)	(0.029)	(0.033)	(0.031)	(0.032)	(0.031)
Observations	62283	59121	59985	56936	59230	56191
Adj. R^2	0.597	0.628	0.670	0.692	0.681	0.702
p-val High = Low	0.022		0.085		0.124	
p-val High > Low	0.011		0.042		0.062	
Panel E: Lotteriness						
Past Optimism x Negative News x Longer Horizon	0.037	0.144***	0.062**	0.192***	0.053**	0.140**
	(0.024)	(0.050)	(0.026)	(0.053)	(0.026)	(0.054)
Observations	97047	24519	93994	23537	93375	22999
Adj. R^2	0.571	0.677	0.643	0.738	0.651	0.753
p-val High = Low	0.029		0.028		0.071	
p-val High > Low	0.015		0.014		0.036	
Panel F: Illiquidity						
Past Optimism x Negative News x Longer Horizon	0.031	0.178***	0.053**	0.232***	0.048*	0.192***
	(0.023)	(0.051)	(0.026)	(0.061)	(0.025)	(0.060)
Observations	95702	26017	92468	25281	92033	24700
Adj. R^2	0.556	0.755	0.630	0.791	0.638	0.808
p-val High = Low	0.002		0.003		0.008	
p-val High > Low	0.001		0.002		0.004	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 7: Mechanism — Stock Ownership. This table shows the results of estimating Eq. (2) in two sub-samples based on whether a certain stock characteristic suggests that the individuals in our sample have a low (columns labeled "Low") or high (columns labeled "High") likelihood of having real financial stakes in stock j. In Panels A and B, stocks with size and price below (above) their respective cross-sectional medians as of the end of the last calendar month prior to day t are categorized as high (low). In Panels C, D and F, the high (low) group comprises stocks with idiosyncratic volatility, idiosyncratic skewness and illiquidity above (below) their respective cross-sectional medians. The cross-sectional medians are based on the full CRSP sample with share codes 10, 11, and 12. In Panel E, the low group captures non-lottery stocks (*Lotteriness* = 0), and the high group captures lottery-type stocks (*Lotteriness* = 1). The sample and control variables used for the analysis are as described under Tables 5. "p-val High = Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High > Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is more concentrated in the "High" group. The construction of the stock characteristics is described in Table A1. Standard errors are clustered at the forecaster and day levels.

Conversely, when the forecaster's knowledge is spread across many industries, the value of the forecaster's knowledge is less dependent on any given industry being successful. So, akin to a standard argument about how portfolio diversification can change agents' incentives, we propose that when knowledge is rather un-diversified and concentrated in a given industry, incentives to maintain optimistic views about that industry grow relative to when knowledge is diversified. Consequently, insofar as optimism shifting arises as a means to protect industry-specific knowledge, it should be stronger when negative news affects stocks in an industry a forecaster has devoted more effort to develop knowledge in.

We measure a forecaster's knowledge stake in the industry of a focal stock based on how focused the forecaster is on that industry. Specifically, we use the number of outstanding, i.e., yet to be terminated, predictions a forecaster has in the industry of the stock hit by negative news as a proxy for the forecaster's knowledge stake in that industry. Next, we classify individuals as having high (low) knowledge stakes in stock j's industry based on whether our knowledge stake proxy is above (below) its cross-sectional median for the year in which the belief-update event takes place. We then compare the extent of optimism shifting in the sample of high versus low knowledge stake. For robustness, we perform the analysis based on alternative industry classifications (SIC three-digit and Fama-French 48 industries). Moreover, we repeat the analysis using an alternative definition of industry focus based on the fraction of predictions that a forecaster has in a given industry rather than the sheer number of such predictions. Finally, we conjecture that industry knowledge can become obsolete over time. Therefore, it is possible that a forecaster's recent focus on an industry is a better indicator of the knowledge stake in that industry. Thus, we also repeat the aforementioned test by measuring industry focus based on a forecaster's activity in the 365-day window ending $t - 1$.

Table 8 summarizes the results. Optimism shifting is always significant at the 1% level in the high-industry focus sample, while it is never statistically significant for the sample of low-industry knowledge stakes. Moreover, the one-sided test of no differences in optimism shifting between the high-industry and low-industry knowledge groups shows that the null is rejected in favor of the alternative that optimism shifting is more pronounced in the high-industry focus in 10 of the 12 specifications at the 1% level, and it is rejected at the 5% level in all tests.

	Future Optimism					
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A						
Past Optimism x Negative News x Longer Horizon	0.029	0.109***	0.055**	0.135***	0.042	0.129***
	(0.024)	(0.035)	(0.027)	(0.039)	(0.026)	(0.037)
Observations	71,581	49,948	68,528	49,100	67,864	48,422
Adj. R^2	0.568	0.684	0.644	0.732	0.655	0.741
p-val High = Low	0.005		0.051		0.035	
p-val High > Low	0.003		0.026		0.018	
Panel B						
Past Optimism x Negative News x Longer Horizon	0.021	0.153***	0.040	0.153***	0.033	0.155***
	(0.024)	(0.035)	(0.026)	(0.039)	(0.027)	(0.037)
Observations	66,773	54,655	63,729	54,090	62,969	53,376
Adj. R^2	0.551	0.697	0.634	0.737	0.645	0.747
p-val High = Low	0.000		0.002		0.002	
p-val High > Low	0.000		0.001		0.001	
Panel C						
Past Optimism x Negative News x Longer Horizon	0.034	0.102***	0.048	0.141***	0.038	0.127***
	(0.026)	(0.030)	(0.030)	(0.035)	(0.030)	(0.034)
Observations	61241	60212	58489	58673	57785	57969
Adj. R^2	0.593	0.643	0.667	0.698	0.678	0.708
p-val High = Low	0.018		0.012		0.012	
p-val High > Low	0.009		0.006		0.006	
Panel D						
Past Optimism x Negative News x Longer Horizon	0.017	0.132***	0.051*	0.116***	0.041	0.112***
	(0.024)	(0.036)	(0.026)	(0.038)	(0.027)	(0.038)
Observations	63,950	57,500	60,850	57,228	60,108	56,541
Adj. R^2	0.553	0.687	0.644	0.719	0.655	0.729
p-val High = Low	0.001		0.058		0.049	
p-val High > Low	0.001		0.029		0.025	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 8: Mechanism — Knowledge Stakes. This table shows the results of estimating Eq. (2) in two sub-samples based on whether the forecaster has a low or high knowledge stake in the industry of stock j. In Panel A, Low (High) knowledge stake is proxied by whether the number of a forecaster's past predictions in the same SIC 3-digit industry as the focal stock j is below (above) the sample median for the calendar year of day $t-1$. Panels B to D offer robustness checks. Panel B repeats the analysis but uses the Fama-French 48-industry classification to assess industry focus; Panel C repeats the analysis but measures industry focus as the ratio of a forecaster's predictions in the same industry of the focal stock over the total number of predictions initiated by the forecaster; Panel D repeats the analysis by measuring industry focus purely based on the forecaster's predictions over the 365 days prior to day $t-1$. The sample and control variables used in the regressions are as described under Tables 5. "p-val High = Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High > Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is more concentrated in the "High" group. Standard errors, in parentheses, are clustered at the forecaster and day levels.

Of course, optimism shifting need not arise just as a tool to protect knowledge about an industry. In fact, when making predictions about a firm, a forecaster is likely to also rely on firm-specific information and knowledge. More so, industry-wide knowledge is reusable across firms in the same industry, and thus less sensitive to the success of any given firm in the industry. On the contrary, firm-specific knowledge is valuable only if the focal firm prospers, and it loses its value if the firm does not. This intuition leads us to hypothesize that the threat to knowledge that negative news about a firm entails can be more severe for firms whose value is less tied to industry and market-wide conditions. If so, a knowledge channel of optimism shifting suggests that optimism shifting should be more likely for stocks whose value is driven more by firm-specific information.

Following the literature (e.g., Chen et al. 2007), we measure the relative importance of firm-specific considerations over industry or market-wide ones for a given stock using the following time-series regression:

$$r_{j,k,t} = a_0 + a_1 r_{mkt,t} + a_2 r_{k,t} + \epsilon_{j,k,t} \tag{3}$$

In Eq. (3), the return of stock j in industry k at time t is explained by the market and industry factors. The extent of firm-specific knowledge embodied in the stock price is reflected in $1 - R^2$ from the regression. We deem this an appropriate measure of the dominance of firm-specific over systematic information since a smaller R^2 indicates that more of the variation in firm value is due to factors that are not shared by other firms in the industry and aggregate market.

We split the belief-update events into two groups based on whether the metric just described is below or above its median value in the cross-section of stocks. If optimism shifting is linked to knowledge stakes, it should be stronger in the group with a high $1 - R^2$ metric.[29] The results reported in Table 9 strongly support the prediction that optimism shifting should increase with the firm-specific information component of a stock's valuation. In all tests, stocks in the group with a large fraction of value linked to firms-specific information exhibit optimism shifting, whereas there is little evidence of optimism shifting among stocks with a small share of firm-specific information driving stock returns. Moreover, in all tests, the null hypothesis of no differences in optimism shifting between the "High" and the "Low" groups is rejected in favor of the one-sided alternative hypothesis that optimism shifting is stronger in the former relative to the latter at the 5% significance level or better. More so, the result is robust to using alternative industry classifications, as well as both equally weighted and value-weighted industry portfolio returns. All in all, the results in this section paint a consistent picture that, similar to financial stakes, knowledge stakes can lead to optimism shifting.

[29] At first sight, this setup seems to resemble our earlier test involving idiosyncratic volatility. However, there are important differences. Idiosyncratic volatility is measured relative to the Fama-French four-factor model, which differs from the regression framework of Eq. (3). Moreover, idiosyncratic volatility need not map closely to $1 - R^2$, as the latter scales idiosyncratic variance by total variance. It is, therefore, unsurprising that the two statistics have a correlation of only 0.375 in our sample, leaving 63% of the variation in the latter metric unexplained by the former.

	Future Optimism					
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: $1-R^2$ based on market and SIC3 industry value-weighted returns						
Past Optimism x Negative News x Longer Horizon	0.015	0.152***	0.027	0.172***	0.017	0.172***
	(0.025)	(0.037)	(0.028)	(0.044)	(0.028)	(0.042)
Observations	80454	41165	77495	39840	76957	39188
Adj. R^2	0.539	0.693	0.624	0.737	0.631	0.753
p-val High = Low	0.004		0.001		0.001	
p-val High > Low	0.002		0.001		0.001	
Panel B: $1-R^2$ based on market and FF48 industry value-weighted returns						
Past Optimism x Negative News x Longer Horizon	0.012	0.133***	0.033	0.140***	0.021	0.152***
	(0.026)	(0.037)	(0.028)	(0.042)	(0.028)	(0.042)
Observations	79324	42242	76418	40824	75851	40143
Adj. R^2	0.536	0.680	0.624	0.725	0.630	0.740
p-val High = Low	0.007		0.010		0.004	
p-val High > Low	0.004		0.005		0.002	
Panel B: $1-R^2$ based on market and SIC3 industry equal-weighted returns						
Past Optimism x Negative News x Longer Horizon	0.031	0.122***	0.053*	0.142***	0.041	0.148***
	(0.026)	(0.035)	(0.028)	(0.041)	(0.028)	(0.040)
Observations	77555	44030	74728	42413	74149	41745
Adj. R^2	0.561	0.676	0.641	0.726	0.649	0.740
p-val High = Low	0.036		0.064		0.047	
p-val High > Low	0.018		0.032		0.024	
Panel C: $1-R^2$ based on market and FF48 industry equal-weighted returns						
Past Optimism x Negative News x Longer Horizon	0.019	0.117***	0.045	0.146***	0.033	0.151***
	(0.026)	(0.036)	(0.028)	(0.043)	(0.029)	(0.041)
Observations	78240	43299	75396	41844	74814	41133
Adj. R^2	0.548	0.675	0.633	0.722	0.640	0.737
p-val High = Low	0.026		0.068		0.043	
p-val High > Low	0.013		0.034		0.022	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 9: Mechanism — Firm-specific Information. This table shows the results of estimating Eq. (2) in two sub-samples based on whether the focal stock j has low (columns labeled "Low") or high (columns labeled "High") firm-specific information, measured as $1-R^2$ from a linear time series regression of a stock's return on that of the market and industry. As the Panel labels indicate, industry classification is based on the SIC 3-digit and Fama-French 48 industry definitions, and the industry returns are either value- or- equal-weighted. A firm is classified as Low (High) firm-specific information if $1-R^2$ is below (above) the cross-sectional median as of the end of the last calendar month prior to day t. The cross-sectional medians are based on the full CRSP sample with share codes 10, 11, 12. The sample and control variables used in the regressions are as described under Tables 5. "p-val High = Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High > Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is more concentrated in the "High" group. Standard errors, in parentheses, are clustered at the forecaster and day levels.

5.3 Confidence Stakes

When a forecaster's optimistic prediction is challenged by incoming information, the forecaster's self-image, defined as the forecaster's own perception of ability, can be at stake. Since theory suggests that individuals with stronger self-image are more likely to engage in the protection of such an image (e.g., Köszegi 2006), we have a straightforward prediction that forecasters who have relatively high self-image have larger stakes than forecasters with weaker self-image. Hence, the former will engage in optimism shifting more than the latter.

To test for the self-image channel of optimism shifting, we need a meaningful measure of self-image that is relevant to the return prediction task and varies by forecaster and over time. Fortunately, CAPS assigns each forecaster on the platform a performance ranking based on the accuracy of forecasters' predictions, which represents a salient measure of one's forecasting ability relative to other platform users. Hence, we argue that the ranking on the platform positively correlates with one's self-image on the return prediction task, and, therefore, optimism shifting should be relatively stronger for the high-ranked forecasters.

We do not have direct access to the full history of rankings published by CAPS. However, CAPS describes how the rankings are constructed, and we follow the description as closely as possible to reproduce the rank of each eligible individual forecaster on CAPS on any given day.[30] Next, we repeat the estimation of the optimism-shifting regression of Eq. (2) in the subsample of low-ranked individuals (i.e., those with low self-image at stake) and high-ranked individuals (i.e., those with high self-image at stake), respectively. Table 10 presents the results. In Panels A and B, the low (high) ranked individuals are those with a performance percentile rank below (above) 50% in the cross-section of ranked CAPS participants as of $t-1$. In Panel C and D, the high-ranked individuals are those with a ranking in the top 25% of the distribution of rankings as of $t-1$, while the rest comprise the low-ranked individuals.

The estimates in Table 10 show that optimism shifting is statistically significant in the sample of high-ranked individuals and not statistically significant in the sample comprising low-ranked individuals. Although the evidence aligns with the intuition that optimism shifting should be more pronounced among individuals with high self-image, statistical tests of the difference in optimism shifting between the high- vs. low-ranked individuals offer mixed evidence in some of the robustness results. Of course, our measure of self-image is only an imperfect proxy for this otherwise unobservable investor characteristic, and we leave a more thorough investigation of this channel to future research.

[30]See Table A1 in the Appendix for more information about the construction of the ranking.

	Future Optimism					
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: SPY-based ranking and 50% threshold						
Past Optimism x Negative News x Longer Horizon	-0.070	0.161***	0.050	0.118***	0.051	0.117***
	(0.050)	(0.035)	(0.053)	(0.036)	(0.053)	(0.035)
Observations	17809	43325	16966	42380	15941	41542
Adj. R^2	0.536	0.707	0.688	0.772	0.703	0.785
p-val High $=$ Low	0.000		0.072		0.093	
p-val High $>$ Low	0.000		0.036		0.047	
Panel B: GSPC-based ranking and 50% threshold						
Past Optimism x Negative News x Longer Horizon	-0.096**	0.172***	0.031	0.121***	0.038	0.122***
	(0.047)	(0.035)	(0.053)	(0.036)	(0.052)	(0.035)
Observations	17573	43550	16645	42675	15583	41853
Adj. R^2	0.523	0.713	0.682	0.776	0.696	0.789
p-val High $=$ Low	0.000		0.054		0.065	
p-val High $>$ Low	0.000		0.027		0.032	
Panel C: SPY-based ranking and 75% threshold						
Past Optimism x Negative News x Longer Horizon	-0.038	0.129***	0.041	0.086**	0.045	0.096**
	(0.043)	(0.040)	(0.046)	(0.039)	(0.048)	(0.039)
Observations	22793	38437	21345	38144	20314	37304
Adj. R^2	0.508	0.738	0.674	0.787	0.687	0.800
p-val High $=$ Low	0.005		0.441		0.463	
p-val High $>$ Low	0.003		0.221		0.232	
Panel D: GSPC-based ranking and 75% threshold						
Past Optimism x Negative News x Longer Horizon	-0.035	0.137***	0.051	0.083**	0.055	0.088**
	(0.043)	(0.040)	(0.046)	(0.039)	(0.047)	(0.038)
Observations	22800	38443	21333	38195	20287	37383
Adj. R^2	0.508	0.741	0.677	0.788	0.690	0.801
p-val High $=$ Low	0.005		0.461		0.513	
p-val High $>$ Low	0.002		0.230		0.256	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 10: Mechanism — Self-Image. This table shows the results of estimating Eq. (2) in two sub-samples based on whether an investor ranks below (for the columns labeled "Low") or above (for the columns labeled "High") the cross-sectional median or 75th percentile of the CAPS forecasters ranking as of $t-1$ where t is the past prediction termination day. The construction of forecaster ranking is described in Table A1. The sample and control variables used in the regressions are as described under Tables 5. "p-val High $=$ Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High $>$ Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is more concentrated in the "High" group. Standard errors are clustered at the level of the forecaster and day.

6 Optimism Shifting and Ex-post Abnormal Returns

In this Section, we investigate the potential implications of optimism shifting for trading performance. We assess whether the expectations of individuals engaging in optimism shifting are less informed and, therefore, followed by lower subsequent abnormal returns. Our analysis is akin to the one in Odean (1998a) on the costs of the disposition effect, and is close to Cookson et al. (2023), who study the return implications of forming beliefs in an echo chamber. We want to compare the performance of traders who maintain their optimism following negative news through optimism shifting with the performance of those who become pessimistic following negative news. So, we focus on the sample of belief update events characterized by negative news and optimistic beliefs prior to the news. Using this sample, we estimate how different belief updates are linked to ex-post abnormal returns using the following regression:

$$\begin{aligned} \textit{Abnormal Return}_{i,j,(t+1\to t+h)} = \textit{Optimist}_{i,j,t}(\beta_1 + \beta_2 \textit{Longer Horizon}_{i,j,t}) \\ + \Gamma\,\mathbf{X}_{i,j,t} + \alpha_i + \gamma_j + \delta_t + \epsilon_{i,j,(t+1\to t+h)}, \end{aligned} \tag{4}$$

where t is the day in which an optimistic forecaster i engages in a belief update event following negative news, *Abnormal Return*$_{i,j,(t+1\to t+h)}$ is the cumulative abnormal return of stock j over the next h subsequent days. Following the literature, e.g., Odean (1998a) and Cookson et al. (2023), the cumulative abnormal return is measured as the stock return minus the CRSP value-weighted market return. *Optimist*$_{i,j,t}$ is a dummy variable that equals one if the forecaster remains optimistic following negative news. *Longer Horizon*$_{i,j,t}$ is a dummy that equals one if the forecaster increases the horizon of their expectation following negative news. $\mathbf{X}$ captures control variables: the longer-horizon dummy, past abnormal returns (*Abnormal Return*$_{i,j,(t-5\to t-1)}$ and *Abnormal Return*$_{i,j,(t-26\to t-6)}$) to control for short-term reversal, and indicator variables for size, book-to-market, and turnover quintiles to rule out concerns that differences in average returns across stock characteristics drive our results. We include forecaster, stock and day fixed effects, and cluster standard errors by stock and day. Clustering by day allows us to account for cross-correlation in returns at the day level. Clustering by stock enables us to account for arbitrary serial correlation at the stock level that can arise from overlapping return windows.[31]

Table 11 summarizes the estimation results. Panel A excludes the controls mentioned earlier; Panel B includes the controls, which we suppress for brevity. Odd-numbered columns exclude *Longer Horizon*$_{i,j,t}$ and its interaction with *Optimist*$_{i,j,t}$ from the specification, focusing on the performance of forecasters that simply retain optimism versus those that revise their beliefs to pessimism. The first observation from the table is that the estimates are stable with

[31] Although Hodrick (1992) suggests an explicit correction for serial correlation, clustering by stock is more conservative, given the result of Thompson (2011) showing that clustering standard errors by stock fully addresses the overlapping returns problem.

and without controls. Focusing on Panel B, we see that remaining optimistic is associated with lower ex-post abnormal returns up to the next 6-month window. The estimates are significant for the 1-week and 1-month windows where underperformance is -0.51% and -1.67%, respectively. For the 9- and 12-month windows, there is a positive and insignificant association between optimism and ex-post abnormal returns.

Turning to our main coefficient of interest, the coefficient of the interaction term $\textit{Optimist}_{i,j,t} \times$ $\textit{Longer Horizon}_{i,j,t}$, we observe negative, sizeable and significant coefficient estimates, indicating that optimism shifting is associated with much higher underperformance relative to simply remaining optimistic about the focal stock. Importantly, the underperformance persists across all the ex-post return windows, amounting to 5.4 and 7.9 percentage points lower returns over three months and one year, respectively.

The regression results provide insights into the investment performance of someone who stays optimistic about a stock but does not engage in optimism shifting. This is captured by the β_1 coefficient, which we find not to be statistically different from zero quite often. Moreover, the magnitude of the coefficient is 2 to 10 times smaller than the coefficient on the interaction term, indicating that the truly harmful form of belief updating for an optimistic forecaster following negative news is not simply remaining optimistic but engaging in optimism shifting. Figure 2 depicts the β_1 coefficient estimates for $\textit{Optimist}_{i,j,t}$ and its sum with that of the interaction term $\textit{Optimist}_{i,j,t} \times \textit{Longer Horizon}_{i,j,t}$ (i.e., $\beta_1 + \beta_2$). The latter captures the overall performance of an optimism shifter. We observe a clear pattern of underperformance associated with optimism shifting, which grows over time, does not reverse, and tends to stabilize after five months.

Overall, the results indicate that while retaining optimism on CAPS following negative news is associated with significant underperformance at shorter horizons, optimism shifting exacerbates the underperformance and extends it to much longer horizons. Therefore, the evidence is consistent with the view that belief updating based on optimism shifting leads to investment mistakes.

	Abnormal Return $(h) \times 100$											
	$h =$ 1-week		$h =$ 1-month		$h =$ 3-month		$h =$ 6-month		$h =$ 9-month		$h =$ 12-month	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Without Controls												
Optimist	-0.667**	-0.518*	-1.905***	-1.593**	-1.058	-0.528	-1.385	-0.719	0.055	0.939	0.591	1.244
	(0.281)	(0.283)	(0.631)	(0.624)	(0.923)	(0.934)	(1.180)	(1.175)	(1.441)	(1.492)	(1.687)	(1.734)
Optimist × Longer Horizon		-1.364*		-3.175**		-5.422**		-6.885**		-8.882**		-6.900*
		(0.820)		(1.414)		(2.256)		(3.256)		(3.661)		(4.083)
Longer Horizon		1.102		3.466***		6.118***		7.849**		9.447***		8.227**
		(0.781)		(1.336)		(2.106)		(3.078)		(3.519)		(3.890)
Forecaster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,588	35,588	35,529	35,529	35,254	35,254	34,789	34,789	34,149	34,149	33,334	33,334
Adj. R^2	0.140	0.140	0.226	0.226	0.299	0.299	0.260	0.260	0.305	0.305	0.284	0.285
Optimist + Optimist × Longer Horizon		-1.881		-4.769		-5.950		-7.604		-7.944		-5.656
p-value		0.021		0.002		0.009		0.022		0.028		0.167
Panel B: With Controls												
Optimist	-0.511*	-0.352	-1.674***	-1.365**	-0.667	-0.129	-0.927	-0.203	0.809	1.816	1.458	2.235
	(0.265)	(0.267)	(0.606)	(0.597)	(0.907)	(0.921)	(1.149)	(1.148)	(1.406)	(1.457)	(1.629)	(1.673)
Optimist × Longer Horizon		-1.451*		-3.145**		-5.481**		-7.395**		-9.993***		-7.961**
		(0.824)		(1.402)		(2.169)		(3.114)		(3.465)		(3.871)
Longer Horizon		1.166		3.379**		6.038***		8.109***		10.195***		8.817**
		(0.780)		(1.324)		(2.026)		(2.944)		(3.335)		(3.673)
Forecaster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,520	35,520	35,461	35,461	35,186	35,186	34,721	34,721	34,081	34,081	33,266	33,266
Adj. R^2	0.151	0.151	0.236	0.236	0.321	0.321	0.297	0.298	0.346	0.346	0.332	0.332
Optimist + Optimist × Longer Horizon		-1.803		-4.510		-5.610		-7.598		-8.177		-5.726
p-value		0.027		0.002		0.010		0.017		0.017		0.140

Table 11: Optimsim Shifting and Future Abnormal Returns. This table summarizes the results of estimating Eq. (4) that regresses the ex-post *Abnormal Return*$_{i,j,(t+1\rightarrow t+h)}$ following individual i's belief update about stock j on day t on an indicator variable for whether the individual remains optimistic about stock j (denoted Optimist) and its interaction with the indicator variable for whether the individual extended their expectation horizon (denoted Longer Horizon). Abnormal returns are computed as stock return minus the CRSP value-weighted market return. The sample includes individuals whose prior beliefs are optimistic and who received negative news. Column headers indicate the abnormal return window h used for the estimation. In parenthesis are standard errors clustered by stock and day.

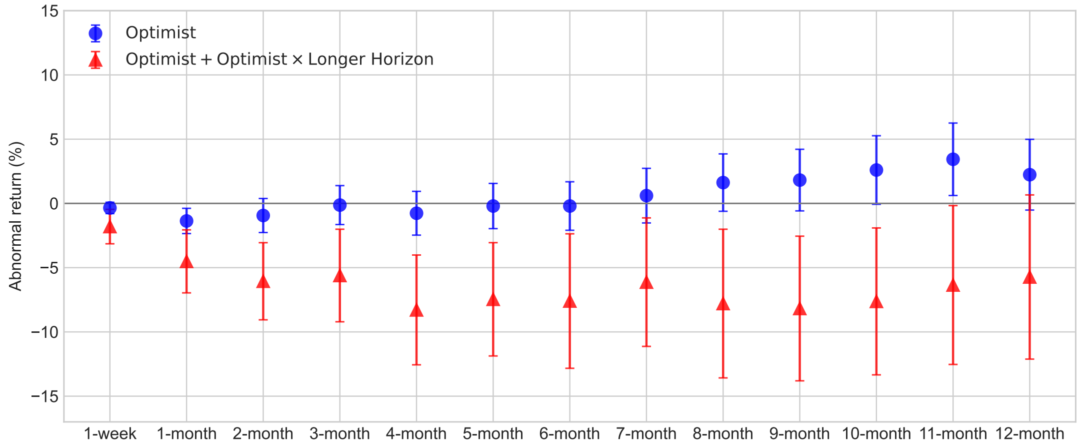


Figure 2: Does Optimism Shifting Result in Lower Ex-post Abnormal Returns? The Figure plots the coefficient estimates and the 90% confidence intervals from estimating Eq. (4) that regresses *Abnormal Return*$_{i,j,(t+1\rightarrow t+h)}$ following individual i's belief update about stock j on day t on an indicator variable for whether the individual remains optimistic about stock j (denoted Optimist) and its interaction with the indicator variable for whether the individual extended their expectation horizon (denoted Longer Horizon). Abnormal returns are computed as stock return minus the CRSP value-weighted market return. The x-axis indicates the abnormal return window h used for the estimation. Standard errors are clustered by stock and day. Further details are in Section 6.

7 Alternative Explanations

7.1 Rational Expectations and Short versus Long-term Market Dynamics

Considering that CAPS forecasters predict a stock's performance relative to the stock market and to the extent that the market exhibits patterns of short-term momentum and long-term reversal (e.g., Poterba and Summers, 1988; Fama and French, 1988), rational expectations could reconcile our optimism shifting results. The argument is as follows. Consider stock j and assume that stock returns follow a simple market model, $R_{j,t} = \beta_j R_{MKT,t} + \epsilon_{j,t}$. Furthermore, assume that the market exhibits patterns of short-term continuation and long-term reversal, i.e., $Corr(R_{MKT,t+1}, R_{MKT,t}) > 0$ and $Corr(R_{MKT,t+T}, R_{MKT,t}) < 0$, for $T > 1$. If the market experiences a negative return today, a stock j with $\beta_j > 1$ is likely to be hit particularly hard, and it underperforms the market. Such underperformance is what our *Negative News* dummy captures. Since the market exhibits short-term positive autocorrelation, this high-beta stock is expected to continue underperforming the market in the short term. At the same time, the market autocorrelation is negative at a long horizon, so that the high-beta stock is expected to outperform the market on a longer horizon. A similar argument suggests stocks with $\beta_j < 1$ underperform the market in the short run when the current market return is positive but outperform on a longer horizon when the market corrects downwards. These patterns of short-term expected underperformance and long-term outperformance could justify optimism shifting.

We conduct empirical tests that probe the merits of the rational-expectations story. Specifically, we build on the evidence that a low (high) valuation of the market strongly predicts higher (lower) market returns over long horizons (e.g., Cochrane 2011). Based on this evidence, rational expectation predicts that optimism shifting should concentrate (i) among high-beta stocks in states of low market valuations and (ii) among low-beta stocks in states of high market valuations. To measure market valuation, we rely on the cyclically adjusted market price-earnings (CAPE) ratio.[32] We then classify the belief-update events in our sample into two groups. The "High LT ER" group corresponds to those update events involving either high-beta stocks in a period of low CAPE or low-beta stocks in periods of high CAPE. The "Others" group contains all other belief-update events. If rational expectations are behind optimism shifting, we expect the bulk of the shifting to occur in the former group, while little or no optimism shifting should be observed in the latter group of events. We test this conjecture by estimating Eq. (2) in the two sub-samples corresponding to predictions in the two aforementioned groups, respectively, and report the results in Table 12.

Panels A, B, and C of Table 12 show results for different definitions of high and low market valuations based on different historical reference levels of CAPE. The results are at odds with the rational-expectations explanation of optimism shifting: there is no evidence of optimism shifting being concentrated among stocks and states suggested by rational expectations. If anything, in all specifications, we find that optimism shifting is stronger in the "Others" sample. Like our earlier evidence showing underperformance due to optimism shifting, the evidence in this Section does not support a rational expectations interpretation of our result.

7.2 Priors

Recent work shows evidence of prior-biased inference in professional analysts' expectations (e.g., Kapons and Kelly, 2022). In our setting, one may wonder whether optimists happen to have tighter priors, resulting in the lower sensitivity to incoming negative news that we

[32] We obtain the data from Robert J. Shiller's website http://www.econ.yale.edu/~shiller/data.htm.

	Future Optimism					
	Others (1)	High LT ER (2)	Others (3)	High LT ER (4)	Others (5)	High LT ER (6)
Panel A: CAPE threshold = past 1-year median						
Past Optimism x Negative News x Longer Horizon	0.074***	0.052*	0.132***	0.070**	0.119***	0.058*
	(0.028)	(0.029)	(0.033)	(0.032)	(0.033)	(0.031)
Observations	61115	60205	58903	58002	58184	57205
Adj. R^2	0.615	0.619	0.682	0.688	0.692	0.698
p-val High = Others	0.392		0.185		0.176	
p-val High > Others	0.804		0.908		0.912	
Panel B: CAPE threshold = past 3-year median						
Past Optimism x Negative News x Longer Horizon	0.077***	0.051*	0.115***	0.062**	0.108***	0.050*
	(0.029)	(0.028)	(0.034)	(0.030)	(0.034)	(0.030)
Observations	60294	60999	58137	58796	57437	57976
Adj. R^2	0.637	0.600	0.701	0.669	0.712	0.678
p-val High = Others	0.535		0.278		0.222	
p-val High > Others	0.732		0.861		0.889	
Panel C: CAPE threshold = full sample median						
Past Optimism x Negative News x Longer Horizon	0.073**	0.056**	0.132***	0.067**	0.112***	0.059**
	(0.029)	(0.028)	(0.031)	(0.031)	(0.033)	(0.030)
Observations	50558	70771	48659	68309	47886	67593
Adj. R^2	0.656	0.592	0.724	0.658	0.737	0.667
p-val High = Others	0.552		0.141		0.123	
p-val High > Others	0.724		0.930		0.938	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 12: Alternative Explanation — Rational Expectations. This table shows the results of estimating Eq. (2) in two sub-samples. Predictions used in the subsample labeled "High LT ER" involve either high-beta ($\beta_j > 1$) stocks in periods of low market valuation or low-beta ($\beta_j < 1$) stocks in periods of high market valuation. All other predictions fall in the "Others" category. We track market valuation using the CAPE ratio and then change the definition of high and low across panels based on the threshold stated in each panel. The thresholds for Panels A and B are computed as of the end of the last calendar month prior to day t. The sample and control variables are the same as described under Table 5. "p-val High = Others" is the p-value for the two-sided test of equality of the reported coefficients across the sub-samples, while "p-val High > Others" tests the null hypothesis that optimism shifting is the same across sub-samples against the alternative one-sided hypothesis of rational expectations that optimism shifting should be stronger in the "High LT ER" sample. Standard errors, in parentheses, are clustered by forecaster and day.

observe in the data. While this may be the case, the informativeness of a forecaster's prior is more naturally linked to a forecaster's decision whether to update his beliefs or not and does not, per se, imply that forecasters will shift their initial optimism to a longer forecast horizon.

That said, we conduct two additional tests that further rule out prior tightness as the primary source of optimism shifting. First, we include forecaster $\times$ stock fixed effects in Eq. (2) to account for the possibility that optimistic forecasters have stock-specific time-invariant prior tightness. The first observation from the result of the analysis shown in column (1) of Table 13 is that the inclusion of forecaster $\times$ stock fixed effects absorbs substantial within forecaster by stock variation in beliefs. As a result, the Adjusted R^2 rises to over 80% and the effective number of observations drops substantially. Notwithstanding, our main result of optimism shifting remains unchanged, as the triple interaction term remains positive and strongly significant.

	Future Optimisim						
		# Focal stock revisions					
	Full Sample	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past Optimism x Negative News x Longer Horizon	0.114***	0.053**	0.061	0.092***	0.078*	0.087***	0.069*
	(0.037)	(0.023)	(0.039)	(0.025)	(0.040)	(0.025)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forecaster x Stock FE	Yes	No	No	No	No	No	No
Day FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	No	Yes	Yes	Yes	Yes
Observations	69553	69576	51991	66364	51761	65704	51143
Adj. R^2	0.811	0.543	0.708	0.639	0.731	0.645	0.743
p-val High = Low		0.833		0.648		0.615	
p-val High > Low		0.416		0.676		0.693	

Table 13: Alternative Explanation — Prior-biased Inference. This table shows the estimates of Eq. (2) that uses an alternative specification and sub-samples of low and high prior belief tightness. In column (1), we include forecaster $\times$ stock fixed effects to the baseline specification. In columns (2) - (7), we conduct sample split for low vs. high prior belief tightness based on whether the number of times a forecaster has revised his predictions on the focal stock j in the past as of $t-1$ is below (columns labeled "Low") or above (columns labeled "High") the yearly sample median. The sample and control variables used in the regressions are the same as described under Tables 5. "'p-val High = Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High > Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is more concentrated in the "High" group. Standard errors, in parentheses, are clustered by forecaster and day.

Second, we go a step further and consider a proxy for the time-varying tightness of a forecaster's prior on a given stock. We follow insights from Augenblick and Rabin (2021), who argue that when a Bayesian learns new information and changes his beliefs, he must, on average, become concomitantly more certain (and hence have more informative priors) about the state of the world. We conjecture that forecasters with a relatively high engagement with a stock through past belief updates are likely to have acquired more information about the stock than those with little engagement with the stock. Hence, we use the number of times a forecaster revised her predictions about the focal stock in the past to measure how tight the forecaster's prior about that stock is. We examine optimism shifting in the sample of forecasters with above- versus below-median number of revisions for the focal stock. Columns (2) - (7) of Table 13 show the results of the analysis, indicating no significant difference in optimism shifting across the two groups. Overall, the results indicate that the tightness of prior beliefs is unlikely to explain the optimism shifting we document.

7.3 Forecaster Experience

Whereas we have cast our discussion of optimism shifting as if it arises due to motivated cognition, it is also possible that it is due to cognitive biases that are due to wired-in heuristics. It is widely believed that cognitive biases are stronger at lower levels of experience and sophistication. In contrast, biases that are due to motivation need not decline with sophistication and can, in fact, increase among investors who are more sophisticated (e.g., Kahan, 2013; Bénabou, 2015). Thus, we argue that one can gauge the origin of optimism shifting by asking whether or not this phenomenon is concentrated among forecasters with low sophistication.

To assess how experience relates to optimism shifting, we proceed in two ways. First, we use forecasters' experiences with the CAPS platform as a proxy for experience with forming expectations about stock returns. We measure a forecaster's experience on CAPS as of a given belief-update event by counting the number of days between the forecaster's first appearance on CAPS and day $t-1$, that is, the day before the prior forecast termination. Next, we group our observations into two sub-samples based on whether a person's experience is below or above the CAPS population's cross-sectional median on the same day. We then estimate Eq. (2) for both sub-samples and report the results in Panel A of Table 14. Comparing the triple interaction term coefficients, we do not observe differences in optimism shifting between the groups.

Second, we use the forecasters' self-reported investing experience, which we obtain from the forecasters' CAPS profiles. Because it is optional to fill out the self-reported experience information, we do not have the information for all individuals. We divide the individuals for whom this piece of information is available into two groups: Low Experience (comprising the *Low* and *Medium* self-reported experience) and High Experience (comprising the *High* self-reported experience). We re-estimate Eq. (2) for both sub-samples and report the results in Panel B of Table 14. Again, there is no evidence that experience reduces optimism shifting. Taken together, the lack of a decline in optimism shifting among the more experienced forecasters suggests that optimism shifting may not be driven by wired-in cognitive biases.

	Future Optimism					
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
Panel A: Forecaster age on CAPS						
Past Optimism x Negative News x Longer Horizon	0.047	0.058*	0.073**	0.078**	0.059*	0.071**
	(0.030)	(0.033)	(0.032)	(0.035)	(0.032)	(0.033)
Observations	36,717	84,540	34,411	83,525	33,525	82,967
Adj. R^2	0.486	0.686	0.599	0.729	0.608	0.738
p-val High = Low	0.910		0.712		0.795	
p-val High > Low	0.455		0.644		0.602	
Panel B: Forecaster stated experience						
Past Optimism x Negative News x Longer Horizon	0.142***	0.067	0.129***	0.110**	0.133***	0.108**
	(0.029)	(0.042)	(0.032)	(0.043)	(0.031)	(0.043)
Observations	51,947	38,711	51,346	39,083	50,539	38,252
Adj. R^2	0.662	0.685	0.720	0.714	0.731	0.724
p-val High = Low	0.209		0.943		0.895	
p-val High > Low	0.896		0.529		0.552	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes

Table 14: Alternative Explanation — Investor Experience. This table shows the estimates of Eq. (2) in two sub-samples of low and high forecaster experience. In Panel A, the Low (High) sample split is based on whether the forecaster's experience on CAPS, i.e., the number of days since the first prediction as of day $t-1$ is below (above) the CAPS sample median. In Panel B, the sample split is based on whether the forecaster's self-reported investing experience is "low" or "medium" (columns labeled "Low") or "high" (columns labeled "High"). The sample and control variables used in the regressions are the same as described under Tables 5. "p-val High = Low" is the p-value for the test of equality of the reported coefficients across the sub-samples. "p-val High > Low" tests the null of no difference between the "High" and "Low" groups against the alternative one-sided hypothesis that optimism shifting is concentrated in the "High" group. Standard errors, in parentheses, are clustered by forecaster and day.

7.4 Extrapolative Beliefs

One of the leading behavioral models of belief formation about stock returns that has gained substantial empirical support is extrapolation (e.g., De Long et al., 1990; Barberis and Shleifer, 2003; Cassella and Gulen, 2018; Da et al., 2021; Nagel and Xu, 2022). Therefore, it seems natural to ask whether optimism shifting stems primarily from extrapolation. This is unlikely for the following reasons: (i) return extrapolation does not embed any notion of forecasters having a preference for optimistic or pessimistic beliefs, nor does it imply a preference for holding certain beliefs over certain horizons; (ii) from a theoretical standpoint, the term structure of extrapolative beliefs is flat across horizons and at all times (Cassella et al., 2022), in that good (bad) recent fundamentals or good recent returns shift expectations up (down) at all horizons. Other richer related models, such as diagnostic expectations (Bordalo et al., 2018), could, in principle, help explain optimism shifting. However, we find this unlikely. This is because diagnostic expectations embed a kernel-of-truth assumption, whereby distortions in expectations about the future arise following incoming information only when such information is, from a rational standpoint, diagnostic about the future. In our main analysis, in which we use weekly stock returns as a proxy for news, recent stock returns are not, from a rational standpoint, very informative about the future value of an asset, especially at long horizons. Therefore, conceptually, it is difficult to reconcile optimism shifting with extrapolation or diagnostic beliefs. Our work suggests that a dynamic and state-contingent form of extrapolation may exist, whereby the reliance of beliefs on past returns or fundamentals may be a function of whether incoming returns and cash-flow realizations align well or not with forecasters' prior beliefs.

8 Conclusion

In this paper, we use data from a social finance platform to document a novel fact about belief updating, which we term optimism shifting. Simply put, when investors who are optimistic about the future value of an asset face negative news about that asset, they hold on to their optimism by actively shifting the optimistic belief to a longer forecast horizon. We hypothesize that individuals' desire to retain their optimistic belief arises due to belief-based utility. We present evidence that is consistent with this interpretation, in that optimism shifting is more likely to arise when a forecaster's stakes in the asset are higher. Besides considering stakes in the more traditional sense of financial ownership, we also demonstrate that an agent's own perception of skill (a confidence channel) and a forecaster's knowledge of the asset (an intangible-stakes channel) can trigger a forecaster's choice to retain optimism through optimism shifting.

Optimism shifting can have important implications for asset pricing and household finance. In the asset pricing literature, optimism shifting can have applications in the literature studying the term structure of equity returns (e.g., Gormsen 2021), since optimism shifting can lead to dynamics in the relative pricing of short-duration and long-duration claims. Optimism shifting can also improve the understanding of some of the dynamics of asset bubbles. In particular, it can help reconcile the evidence that during bubbles, prices can remain high for some time even after the arrival of negative news, such as reports of overvaluation from experts (e.g., Barberis, 2018). In the household finance literature, optimism shifting could help explain the disposition effect (Odean 1998b), which embodies investors' tendency to hold onto losing investments too long. These applications represent some of the interesting avenues our work sets the stage for, and we leave these avenues to future research.

References

Affleck-Graves, J. and Mendenhall, R. R. (1992). The relation between the value line enigma and post-earnings-announcement drift. *Journal of Financial Economics*, 31(1):75–96.

Afrouzi, H., Kwon, S. Y., Landier, A., Ma, Y., and Thesmar, D. (2020). Overreaction in expectations: Evidence and theory. *Available at SSRN*.

Akerlof, G. A. and Dickens, W. T. (1982). The economic consequences of cognitive dissonance. *The American Economic Review*, 72(3):307–319.

Amelio, A. and Zimmermann, F. (2023). Motivated memory in economics—a review. *Games*, 14(1):15.

Andries, M. and Haddad, V. (2020). Information aversion. *Journal of Political Economy*, 128(5):1901–1939.

Augenblick, N. and Rabin, M. (2021). Belief movement, uncertainty reduction, and rational updating. *The Quarterly Journal of Economics*, 136(2):933–985.

Avery, C. N., Chevalier, J. A., and Zeckhauser, R. J. (2016). The "caps" prediction system and stock market returns. *Review of Finance*, 20(4):1363–1381.

Banerjee, S., Davis, J., and Gondhi, N. (2020). The man (ager) who knew too much. *Available at SSRN 3490117*.

Banerjee, S., Davis, J., and Gondhi, N. (2023). Choosing to disagree: Endogenous dismissiveness and overconfidence in financial markets. *The Journal of Finance, Forthcoming*.

Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2):773–806.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics*, 116(1):261–292.

Barberis, N. (2018). Psychology-based models of asset prices and trading volume. In *Handbook of behavioral economics: applications and foundations 1*, volume 1, pages 79–175. Elsevier.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015). X-capm: An extrapolative capital asset pricing model. *Journal of financial economics*, 115(1):1–24.

Barberis, N. and Shleifer, A. (2003). Style investing. *Journal of Financial Economics*, 68(2):161–199.

Bénabou, R. (2013). Groupthink: Collective delusions in organizations and markets. *Review of economic studies*, 80(2):429–462.

Bénabou, R. (2015). The economics of motivated beliefs. *Revue d'économie politique*, 125(5):665–685.

Bénabou, R. and Tirole, J. (2016). Mindful economics: The production, consumption, and value of beliefs. *Journal of Economic Perspectives*, 30(3):141–64.

Bøler, E. A., Moxnes, A., and Ulltveit-Moe, K. H. (2015). R&d, international sourcing, and the joint impact on firm performance. *American Economic Review*, 105(12):3704–3739.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2018). Diagnostic expectations and credit cycles. *The Journal of Finance*, 73(1):199–227.

Bradley, D., Hanousek Jr, J., Jame, R., and Xiao, Z. (2021). Place your bets? the market consequences of investment research on reddit's wallstreetbets. *Available at SSRN*.

Brunnermeier, M. K. and Parker, J. A. (2005). Optimal expectations. *American Economic Review*, 95(4):1092–1118.

Bénabou, R. and Tirole, J. (2002). Self-Confidence and Personal Motivation*. *The Quarterly Journal of Economics*, 117(3):871–915.

Camerer, C., Loewenstein, G., and Weber, M. (1989). The curse of knowledge in economic settings: An experimental analysis. *Journal of political Economy*, 97(5):1232–1254.

Caplin, A. and Leahy, J. (2001). Psychological expected utility theory and anticipatory feelings. *The Quarterly Journal of Economics*, 116(1):55–79.

Caplin, A. and Leahy, J. V. (2019). Wishful thinking. Technical report, National Bureau of Economic Research.

Cassella, S., Golez, B., Gulen, H., and Kelly, P. (2021). Horizon bias in expectations formation. *Available at SSRN 3759035*.

Cassella, S., Golez, B., Gulen, H., and Kelly, P. (2022). Motivated beliefs in macroeconomic expectations. *Available at SSRN 3759035*.

Cassella, S., Golez, B., Gulen, H., and Kelly, P. (2023). Horizon bias and the term structure of equity returns. *The Review of Financial Studies*, 36(3):1253–1288.

Cassella, S. and Gulen, H. (2018). Extrapolation bias and the predictability of stock returns by price-scaled variables. *The Review of Financial Studies*, 31(11):4345–4397.

Charness, G. and Dave, C. (2017). Confirmation bias with motivated beliefs. *Games and Economic Behavior*, 104:1–23.

Charness, G., Rustichini, A., and Van de Ven, J. (2018). Self-confidence and strategic behavior. *Experimental Economics*, 21:72–98.

Chen, H., De, P., Hu, Y. J., and Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5):1367–1403.

Chen, Q., Goldstein, I., and Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *The Review of Financial Studies*, 20(3):619–650.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, 66(4):1047–1108.

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2023). Echo chambers. *The Review of Financial Studies*, 36(2):450–500.

Cookson, J. A., Lu, R., Mullins, W., and Niessner, M. (2022). The social signal. *Available at SSRN*.

Cookson, J. A. and Niessner, M. (2020). Why don't we agree? evidence from a social network of investors. *The Journal of Finance*, 75(1):173–228.

Crouzet, N., Eberly, J. C., Eisfeldt, A. L., and Papanikolaou, D. (2022). The economics of intangible capital. *Journal of Economic Perspectives*, 36(3):29–52.

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Darley, J. M. and Gross, P. H. (1983). A hypothesis-confirming bias in labeling effects. *Journal of Personality and Social Psychology*, 44(1):20.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *The Journal of Finance*, 45(2):379–395.

Dim, C. (2020). Social media analysts' skills: Insights from text-implied beliefs. *Available at SSRN 3813252*.

Doraszelski, U., Lewis, G., and Pakes, A. (2018). Just starting out: Learning and equilibrium in a new market. *American Economic Review*, 108(3):565–615.

Eil, D. and Rao, J. M. (2011). The good news-bad news effect: asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics*, 3(2):114–138.

Eisfeldt, A. L. and Papanikolaou, D. (2014). The value and ownership of intangible capital. *American Economic Review*, 104(5):189–194.

Eliaz, K. and Spiegler, R. (2006). Contracting with diversely naive agents. *The Review of Economic Studies*, 73(3):689–714.

Fama, E. F. and French, K. R. (1988). Permanent and temporary components of stock prices. *Journal of Political Economy*, 96(2):246–273.

Farrell, M., Green, T. C., Jame, R., and Markov, S. (2021). The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics*.

Fryer Jr, R. G., Harms, P., and Jackson, M. O. (2019). Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. *Journal of the European Economic Association*, 17(5):1470–1501.

Gentzkow, M. and Shapiro, J. M. (2010). What drives media slant? evidence from us daily newspapers. *Econometrica*, 78(1):35–71.

Goetzmann, W. N. and Kumar, A. (2008). Equity portfolio diversification. *Review of Finance*, 12(3):433–463.

Golman, R., Hagmann, D., and Loewenstein, G. (2017). Information avoidance. *Journal of economic literature*, 55(1):96–135.

Gormsen, N. J. (2021). Time variation of the equity term structure. *The Journal of Finance*, 76(4):1959–1999.

Greenwood, R. and Shleifer, A. (2014). Expectations of Returns and Expected Returns. *The Review of Financial Studies*, 27(3):714–746.

Hartzmark, S. M., Hirshman, S. D., and Imas, A. (2021). Ownership, learning, and beliefs. *The Quarterly Journal of Economics*, 136(3):1665–1717.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of Finance*, 55(3):1263–1295.

Heimer, R. Z. (2016). Peer pressure: Social interaction and the disposition effect. *The Review of Financial Studies*, 29(11):3177–3209.

Hirshleifer, D., Peng, L., and Wang, Q. (2023). News diffusion in social networks and stock market reactions. Technical report, National Bureau of Economic Research.

Hodrick, R. J. (1992). Dividend yields and expected stock returns: Alternative procedures for inference and measurement. *The Review of Financial Studies*, 5(3):357–386.

Jackson, A. R. (2005). Trade generation, reputation, and sell-side analysts. *The Journal of Finance*, 60(2):673–717.

Johnson, D. D. and Fowler, J. H. (2011). The evolution of overconfidence. *Nature*, 477(7364):317–320.

Kahan, D. M. (2013). Ideology, motivated reasoning, and cognitive reflection. *Judgment and Decision making*, 8(4):407–424.

Kakhbod, A., Kazempour, S. M., Livdan, D., and Schuerhoff, N. (2023). Finfluencers. *Available at SSRN 4428232*.

Kapons, M. M. and Kelly, P. (2022). Biased inference due to prior beliefs: Evidence from the field. *Available at SSRN 4209631*.

Karlsson, N., Loewenstein, G., and Seppi, D. (2009). The ostrich effect: Selective attention to information. *Journal of Risk and uncertainty*, 38:95–115.

Köszegi, B. (2006). Ego utility, overconfidence, and task choice. *Journal of the European Economic Association*, 4(4):673–707.

Kuhnen, C. M. (2015). Asymmetric learning from financial information. *The Journal of Finance*, 70(5):2029–2062.

Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, 64(4):1889–1933.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1):1–28.

Levy, H., Rossi, A. G., Shalev, R., and Zur, E. (2023). What's in investors' information set? *Available at SSRN 4068922*.

Li, K., Mai, F., Shen, R., and Yan, X. (2021). Measuring corporate culture using machine learning. *The Review of Financial Studies*, 34(7):3265–3315.

Lim, T. (2001). Rationality and analysts' forecast bias. *The journal of Finance*, 56(1):369–385.

Lin, H.-w. and McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of accounting and economics*, 25(1):101–127.

Livnat, J. and Mendenhall, R. R. (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of accounting research*, 44(1):177–205.

Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *The Economic Journal*, 97(387):666–684.

Lord, C. G., Ross, L., and Lepper, M. R. (1979). Biased assimilation and attitude polarization: The effects of prior theories on subsequently considered evidence. *Journal of personality and social psychology*, 37(11):2098.

Mankiw, N. G. and Reis, R. (2002). Sticky information versus sticky prices: a proposal to replace the new keynesian phillips curve. *The Quarterly Journal of Economics*, 117(4):1295–1328.

Michaely, R. and Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies*, 12(4):653–686.

Mitton, T. and Vorkink, K. (2007). Equilibrium underdiversification and the preference for skewness. *The Review of Financial Studies*, 20(4):1255–1288.

Möbius, M. M., Niederle, M., Niehaus, P., and Rosenblat, T. S. (2022). Managing self-confidence: Theory and experimental evidence. *Management Science*, 68(11):7793–7817.

Nagel, S. and Xu, Z. (2022). Asset pricing with fading memory. *The Review of Financial Studies*, 35(5):2190–2245.

Nisbett, R. E. and Ross, L. (1980). *Human Inference: Strategies and Shortcomings of Social Judgment*. Englewood Cliffs, NJ, USA: Prentice-Hall.

Odean, T. (1998a). Are investors reluctant to realize their losses? *The Journal of Finance*, 53(5):1775–1798.

Odean, T. (1998b). Are investors reluctant to realize their losses? *The Journal of finance*, 53(5):1775–1798.

Odean, T. (1998c). Volume, volatility, price, and profit when all traders are above average. *The journal of finance*, 53(6):1887–1934.

Oster, E., Shoulson, I., and Dorsey, E. (2013). Optimal expectations and limited medical testing: Evidence from huntington disease. *American Economic Review*, 103(2):804–30.

Pástor, L. and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3):642–685.

Poterba, J. M. and Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of financial economics*, 22(1):27–59.

Puri, M. and Robinson, D. T. (2007). Optimism and economic choice. *Journal of Financial Economics*, 86(1):71–99.

Rabin, M. and Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, 114(1):37–82.

Reed, W. R. (2015). On the practice of lagging variables to avoid simultaneity. *Oxford Bulletin of Economics and Statistics*, 77(6):897–905.

Scheier, M. F. and Carver, C. S. (1985). Optimism, coping, and health: assessment and implications of generalized outcome expectancies. *Health psychology*, 4(3):219.

Schulz, R., Bookwala, J., Knapp, J. E., Scheier, M. F., and Williamson, G. M. (1999). Pessimism, age, and cancer mortality.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of financial Economics*, 99(1):1–10.

Veldkamp, L. (2023). Valuing data as an asset. *Review of Finance*, page rfac073.

Veldkamp, L. and Chung, C. (2019). Data and the aggregate economy. *Journal of Economic Literature*.

Von Hippel, W. and Trivers, R. (2011). The evolution and psychology of self-deception. *Behavioral and brain sciences*, 34(1):1–16.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of personality and social psychology*, 39(5):806.

Woodford, M. (2001). Imperfect common knowledge and the effects of monetary policy.

Zimmermann, F. (2020). The dynamics of motivated beliefs. *American Economic Review*, 110(2):337–61.

A Appendix

Table A1: Description of Variables used in this Study

Variable	Definition
Future Optimism	An indicator variable that captures the bullishness of individual i's belief expressed on day $t+\tau$ about stock j's future return relative to that of the S&P 500 index. The variable equals one if the prediction is that stock j will outperform the S&P 500 index and zero otherwise.
Past Optimism	An indicator variable that captures the bullishness of individual i's outstanding belief about stock j terminated on day t before the initiation of a new prediction on day $t+\tau$. The variable equals one if an individual predicts that stock j will outperform the S&P 500 index and zero otherwise.
Negative News	An indicator variable that equals one if stock j's return over the past one week period (five trading days) ending $t-1$ is less than that of the benchmark over the same period: $$\textit{Negative News}_{i,j,t-\tau} = \mathbb{1}\left(\sum_{s=t-5-\tau}^{t-\tau} \textit{Ret}_{j,s} < \sum_{s=t-5-\tau}^{t-\tau} R_{b,s}\right)$$ where $\textit{Ret}_{j,s}$ is stock j's log return on day s and $R_{b,s}$ is log return of the benchmark S&P 500 index on day s. The benchmark index is primarily the SPY ETF. For robustness, we also use the S&P 500 ˆGSPC as the benchmark or simply set the benchmark return to zero so that negative news depends only on whether stocks' realized returns are negative or not.
Negative News (Weighted)	An indicator variable that equals one if stock j's exponentially weighted raw return, ex-SPY, or ex-GSPC return is negative and zero otherwise, respectively. The exponentially weighted returns build on the framework of Da et al. (2021) and are computed as a weighted average return of past 12 non-overlapping weekly returns, i.e., three months' worth of past return realizations ending $t-1$. The weight for a given prior week $s \in [1, 2, ..., 12]$ return is given by $w_s = \frac{\lambda^{s-1}}{\sum_{j=1}^{12} \lambda^{j-1}}$, where we set the parameter $\lambda = 0.59$ based on the estimates in Da et al. (2021).
Negative News (SUE)	An indicator variable that equals one if a negative earnings surprise is reported for stock j within the past 30-day window ending $t-1$. Earnings surprise is defined as Standardized Unexpected Earnings (SUE), measured as the difference between quarterly earnings per share (EPS) and the average of analysts' EPS forecast for that quarter, then divided by the stock price at the end of the previous quarter.
Ftr. Negative News	Future negative news computed as the ex-SPY based Negative News measure described above, but calculated over the five-day window starting $t+1$, where t is the past prediction termination day.

Longer Horizon	An indicator variable that captures whether the horizon of an individual's new prediction about stock j on day $t+\tau$ is higher than that of the old prediction on the same stock. It equals one if the horizon of "Future Optimism" is longer than that of "Past Optimism" and zero otherwise.
Horizon Change (Years)	Difference in years between the horizons of new and old prediction on the same stock. To construct it, we translate categorical horizon variables into years; e.g., three-week = 0.06 years, three-month = 0.25 years.
Horizon Change (Rank)	Difference in rank between the horizons of new and old prediction on the same stock. To construct it, we rank the categorical horizon labels in ascending order from 1 for the three-week horizon to 5 for the five-year horizon.
Portfolio Optimism	The average optimism of one's portfolio of outstanding predictions. To obtain the average, predictions that a stock will outperform the S&P 500 index are coded as 1, while underperform predictions are coded as 0. Unless otherwise stated, an individual's portfolio of outstanding predictions comprises predictions on other stocks, *excluding* the focal stock j, that have not been terminated as of $t-1$, where t is the termination day of focal stock j's prediction.
Number of Picks	The number of stocks in an individual's portfolio of outstanding predictions as defined under Portfolio Optimism.
Portfolio Ex-market Ret.	The signed ex-SPY return (defined under Negative News) averaged across a forecaster's portfolio of outstanding predictions as of day $t-1$, where t is the past prediction termination day.
Log(CAPS Age)	The natural log of a forecaster's age (in years) on CAPS as of $t-1$, where t is the past prediction termination day. We obtain age as the number of years since the forecaster's first prediction on CAPS.
Industry Knowledge	We proxy a forecaster's knowledge stake in the industry of focal stock j using the concentration of her predictions in that industry as of $t-1$, where t is the past prediction termination day. We use different industry concentration measures: (i) the number of outstanding predictions a forecaster has in the same three-digit SIC code as stock j; (ii) the number of outstanding predictions a forecaster has in the same Fama-French 48 industry as stock j; (iii) the number of predictions a forecaster initiated in the same three-digit SIC code industry as stock j over the past one year; (iv) the number of outstanding predictions a forecaster has in the same three-digit SIC code as stock j divided by the total number of outstanding predictions.

Forecaster Performance Rank	We construct a person's performance rank (i.e., CAPS rating) in the prediction task relative to other CAPS forecasters as of day $t-1$, where t is the past prediction termination day, as closely as possible following the description on the CAPS platform. We summarize the construction here and refer interested readers to the CAPS help page for a full description. A person's performance rank as of a generic time t depends on the weighted sum of her *Score rank* and *Accuracy rank*. "Score" is the sum of the ex-SPY stock returns one has accumulated in each individual stock prediction up to t, including active predictions and accumulated returns for all ended predictions as of when they were ended. The ex-SPY stock returns for "Underperform" predictions are appropriately signed by pre-multiplying them by -1. "Accuracy" measures how often one makes correct predictions, computed as the number of correct predictions divided by the total number of predictions as of day t. A correct prediction is one for which the signed cumulative ex-SPY return as of t is greater than zero. Next, *Score rank* and *Accuracy rank* as of t are obtained as each person's percentile rank on "Score" and "Accuracy", respectively, relative to other CAPS forecasters with at least seven active predictions. Next, a forecaster's "Raw rating" as of t is obtained as $(2/3 \times \textit{Score rank}) + (1/3 \times \textit{Accuracy rank})$. Finally, the forecaster's performance rank as of t is obtained as her percentile rank on "Raw rating" relative to other CAPS forecasters. To receive a performance rank on any given day t, a forecaster must have at least seven active predictions.

Stock Characteristics

CAPS Consensus	The average optimism across all outstanding, i.e., active (not yet terminated) predictions on stock j computed as of the end of the last calendar month prior to day t. To obtain the average, predictions that a stock will outperform (underperform) the S&P 500 index are coded as 1 (0). If there is no outstanding prediction on a stock to compute the average, the variable is set to the neutral value of 0.5.
Size	A stock's market capitalization as of the end of the last calendar month prior to day t.
Log(Market Cap.)	The natural log of a stock's market capitalization as of the end of the last calendar month prior to day t.
Log(Book-to-Market)	The natural log of a stock's book-to-market ratio computed as of the end of the calendar year prior to day t. We follow common practice and add a buffer period of six months to the date of fundamental release to ensure the information is observable to market participants.
Price	Stock price per share as of the end of the last calendar month prior to day t.
Idio. Volatility	Idiosyncratic volatility computed as of the end of the last calendar month prior to day t. It is calculated as in Kumar (2009) based on the standard deviation of return residuals relative to the Carhart four-factor model using six months of daily returns data. We require a minimum of three months of data.

Idio. Skewness	Idiosyncratic skewness computed as of the end of the last calendar month prior to day t. It is computed as in Kumar (2009) based on the normalized third central moment of return residuals obtained by fitting the two-factor model of Harvey and Siddique (2000) using six months of daily returns data, where the two factors are the excess market returns and the squared excess market returns. We require a minimum of three months of data.
Lotteriness	An indicator variable that captures whether a stock is a lottery-type asset as of the end of the last calendar month as in Kumar (2009). The variable equals one if stock j's price per share is below the 50^{th} percentile and its idiosyncratic volatility and idiosyncratic skewness are above their respective 50^{th} percentiles, otherwise zero. The ranking is based on the cross-section of CRSP common stocks.
Illiquidity	Amihud illiquidity as of the end of the last calendar month prior to day t. It is measured as the absolute daily returns per unit of trading volume and is averaged over the past six months period and normalized by the monthly cross-sectional mean. We require a minimum of three months of data.
CAPM Beta	The CAPM market beta of a stock computed as of the end of the last calendar month prior to day t using six months of daily returns data. We require a minimum of three months of daily data.
$1 - R^2$	Measures firm-specific information in a stock's price as of the end of the last calendar month prior to day t following Chen et al. (2007). We regress a stock's daily returns on market and industry returns using one year of daily returns data. We then subtract the regression R^2 from 1. We require a minimum of three months of daily data.

Table A2: First-Stage Results for 2SLS Estimation of Optimism Shifting. This table shows first-stage results for the instrumental variable estimation that uses the past prediction horizon (in years) as the primary instrument for the longer horizon dummy variable. Accordingly, the interaction of the longer horizon dummy and a predetermined variable is instrumented by the interaction of primary instrument and the predetermined variable. The column headers indicate the endogenous variables, where LH stands for Longer Horizon, PO denotes Past Optimisim, and NN denotes Negative News.

	Panel A											
	(1) LH	(2) PO x LH	(3) NN x LH	(4) PO x NN x LH	(5) LH	(6) PO x LH	(7) NN x LH	(8) PO x NN x LH	(9) LH	(10) PO x LH	(11) NN x LH	(12) PO x NN x LH
Past Horizon	-0.075***	0.003***	0.005***	0.002***	-0.074***	0.004***	0.005***	0.002***	-0.077***	0.003***	0.003***	0.002***
	(0.005)	(0.000)	(0.001)	(0.000)	(0.005)	(0.001)	(0.001)	(0.000)	(0.004)	(0.001)	(0.001)	(0.000)
Past Optimism x Past Horizon	0.012**	-0.067***	-0.003***	-0.001***	0.011**	-0.068***	-0.003***	-0.001***	0.012***	-0.068***	-0.003***	-0.001**
	(0.005)	(0.004)	(0.001)	(0.000)	(0.004)	(0.004)	(0.001)	(0.000)	(0.004)	(0.004)	(0.001)	(0.000)
Negative News x Past Horizon	0.021***	-0.000	-0.061***	-0.000	0.020***	-0.000	-0.062***	-0.000	0.019***	-0.000	-0.063***	-0.000
	(0.004)	(0.000)	(0.005)	(0.000)	(0.003)	(0.000)	(0.005)	(0.000)	(0.003)	(0.000)	(0.005)	(0.000)
Past Optimism x Negative News x Past Horizon	-0.024***	-0.002	-0.006	-0.067***	-0.023***	-0.002	-0.006	-0.068***	-0.022***	-0.002	-0.006	-0.069***
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.003)	(0.006)	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)
Past Optimism	-0.096***	0.333***	-0.010***	-0.003**	-0.092***	0.338***	-0.010***	-0.002	-0.098***	0.340***	-0.014***	-0.002
	(0.021)	(0.020)	(0.003)	(0.001)	(0.019)	(0.019)	(0.004)	(0.002)	(0.018)	(0.018)	(0.004)	(0.002)
Negative News	-0.093***	0.005***	0.318***	0.004***	-0.088***	0.006***	0.321***	0.003***	-0.084***	0.005***	0.327***	0.003**
	(0.017)	(0.001)	(0.023)	(0.001)	(0.016)	(0.002)	(0.022)	(0.001)	(0.015)	(0.002)	(0.022)	(0.001)
Past Optimism x Negative News	0.106***	0.010	0.035	0.351***	0.102***	0.011	0.035	0.354***	0.099***	0.012	0.032	0.357***
	(0.026)	(0.019)	(0.029)	(0.023)	(0.023)	(0.016)	(0.027)	(0.021)	(0.022)	(0.015)	(0.026)	(0.020)
Ftr. Negative News	0.003	0.002	0.002*	0.001	0.002	0.001	0.002	0.000	0.002	0.001	0.002	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Log(Number of Picks)	-0.017***	-0.006**	-0.010***	-0.004**	-0.017***	-0.007***	-0.010***	-0.004**	-0.014***	-0.006**	-0.008***	-0.003*
	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Portfolio Optimism	0.074***	0.013	0.046***	0.006	0.078***	0.011	0.048***	0.004	0.081***	0.015*	0.048***	0.006
	(0.017)	(0.009)	(0.011)	(0.005)	(0.016)	(0.009)	(0.011)	(0.005)	(0.015)	(0.009)	(0.009)	(0.005)
Portfolio Ex-market Ret.	-0.065	-0.088	0.007	0.002	-0.070	-0.090	0.022	0.024	-0.067	-0.084	0.024	0.028
	(0.078)	(0.067)	(0.042)	(0.034)	(0.093)	(0.079)	(0.046)	(0.039)	(0.085)	(0.073)	(0.043)	(0.036)
CAPS Consensus	0.023**	0.012***	0.013*	0.007**	0.029***	0.013***	0.017**	0.008***	0.035**	0.015	0.023*	0.011*
	(0.010)	(0.004)	(0.007)	(0.003)	(0.009)	(0.004)	(0.007)	(0.003)	(0.017)	(0.009)	(0.012)	(0.006)
Log(Market Cap.)	0.005***	0.002***	0.003***	0.001**	0.005***	0.002***	0.003***	0.001***	0.001	-0.002*	0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Log(Book-to-Market)	0.000	0.001*	0.001	0.000*	0.001	0.001*	0.001	0.001**	0.001*	0.000	0.001*	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
CAPM Beta	-0.005**	-0.004***	-0.004**	-0.003***	-0.005**	-0.004***	-0.004**	-0.003***	-0.003	-0.003*	-0.003**	-0.002***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Log(CAPS Age)	-0.003***	-0.003***	-0.002***	-0.001***	-0.003**	-0.001	-0.002**	-0.001	-0.003**	-0.001	-0.002**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Day FE	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Forecaster FE	No	No	No	No	No	No	No	No	No	No	No	No
Stock x Month FE	No	No	No	No	No	No	No	No	No	No	No	No
Observations	123,117	123,117	123,117	123,117	123,055	123,055	123,055	123,055	122,506	122,506	122,506	122,506

Continues

	Panel B											
	(13) LH	(14) PO x LH	(15) NN x LH	(16) PO x NN x LH	(17) LH	(18) PO x LH	(19) NN x LH	(20) PO x NN x LH	(21) LH	(22) PO x LH	(23) NN x LH	(24) PO x NN x LH
Past Horizon	-0.115***	-0.023***	-0.023***	-0.011***	-0.117***	-0.024***	-0.025***	-0.011***	-0.123***	-0.023***	-0.028***	-0.011***
	(0.005)	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)
Past Optimism x Past Horizon	-0.003	-0.077***	-0.004**	-0.005***	-0.003	-0.078***	-0.004*	-0.005***	-0.004	-0.084***	-0.004	-0.007***
	(0.004)	(0.005)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)
Negative News x Past Horizon	0.012***	0.003**	-0.061***	0.002***	0.011***	0.003**	-0.061***	0.002***	0.010***	0.004***	-0.065***	0.003***
	(0.003)	(0.001)	(0.005)	(0.001)	(0.003)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.005)	(0.001)
Past Optimism x Negative News x Past Horizon	-0.013***	-0.006**	-0.006	-0.071***	-0.013***	-0.006**	-0.006	-0.072***	-0.012***	-0.008**	-0.005	-0.076***
	(0.004)	(0.002)	(0.005)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)
Past Optimism	-0.004	0.373***	0.009	0.016**	-0.011	0.375***	0.004	0.015**	-0.020	0.389***	0.002	0.020***
	(0.016)	(0.023)	(0.009)	(0.006)	(0.016)	(0.022)	(0.009)	(0.006)	(0.020)	(0.022)	(0.011)	(0.008)
Negative News	-0.056***	-0.011*	0.308***	-0.009**	-0.054***	-0.011**	0.312***	-0.009***	-0.049***	-0.020***	0.332***	-0.013***
	(0.013)	(0.006)	(0.023)	(0.003)	(0.013)	(0.006)	(0.022)	(0.003)	(0.014)	(0.007)	(0.023)	(0.005)
Past Optimism x Negative News	0.066***	0.029**	0.041*	0.365***	0.066***	0.030***	0.041*	0.368***	0.065***	0.040***	0.035	0.385***
	(0.016)	(0.012)	(0.025)	(0.022)	(0.016)	(0.012)	(0.024)	(0.022)	(0.020)	(0.014)	(0.025)	(0.023)
Ftr. Negative News	0.001	0.000	0.001	0.000	0.001	0.000	0.001	-0.000	0.003	-0.000	0.003*	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)
Log(Number of Picks)	-0.001	0.004	-0.004	0.002	-0.000	0.004	-0.003	0.002	-0.000	0.002	-0.002	0.001
	(0.006)	(0.005)	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)	(0.003)
Portfolio Optimism	0.026	-0.022	0.014	-0.017*	0.029	-0.020	0.015	-0.016*	0.042**	-0.009	0.024	-0.007
	(0.023)	(0.015)	(0.016)	(0.009)	(0.021)	(0.014)	(0.014)	(0.008)	(0.021)	(0.015)	(0.015)	(0.010)
Portfolio Ex-market Ret.	0.088	0.041	0.111***	0.079***	0.082	0.040	0.112***	0.080***	0.067	0.049	0.071*	0.051**
	(0.058)	(0.039)	(0.038)	(0.029)	(0.056)	(0.039)	(0.037)	(0.029)	(0.057)	(0.032)	(0.038)	(0.025)
CAPS Consensus	0.052***	0.030***	0.028***	0.015***	0.055***	0.029***	0.037***	0.018***				
	(0.008)	(0.005)	(0.006)	(0.003)	(0.014)	(0.010)	(0.011)	(0.006)				
Log(Market Cap.)	0.003***	0.001***	0.002***	0.001***	-0.002	-0.003**	-0.001	-0.002**				
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)				
Log(Book-to-Market)	-0.000	-0.000	-0.000	0.000	-0.001	-0.001*	-0.000	-0.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)				
Market Beta	-0.005***	-0.003***	-0.004***	-0.002***	-0.004**	-0.002*	-0.004***	-0.002**				
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)				
Log(CAPS Age)												
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Stock FE	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	No
Forecaster FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock x Month FE	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Observations	119,268	119,268	119,268	119,268	118,706	118,706	118,706	118,706	84,669	84,669	84,669	84,669

	Future Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Longer Horizon	0.084***	0.078***	0.071***	0.094***	0.086***	0.093***
	(0.025)	(0.024)	(0.023)	(0.025)	(0.024)	(0.028)
Past Optimism x Negative News	0.078***	0.077***	0.076***	0.063***	0.063***	0.048***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Negative News	-0.138***	-0.135***	-0.129***	-0.116***	-0.112***	-0.074***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.013)
Past Optimism	0.468***	0.455***	0.402***	0.423***	0.370***	0.247***
	(0.034)	(0.033)	(0.029)	(0.040)	(0.034)	(0.030)
Longer Horizon	0.316***	0.314***	0.298***	0.306***	0.287***	0.233***
	(0.026)	(0.025)	(0.022)	(0.030)	(0.026)	(0.026)
Past Optimism x Longer Horizon	-0.314***	-0.306***	-0.284***	-0.293***	-0.271***	-0.209***
	(0.030)	(0.029)	(0.025)	(0.034)	(0.029)	(0.028)
Negative News x Longer Horizon	-0.073***	-0.070***	-0.064***	-0.093***	-0.085***	-0.086***
	(0.024)	(0.023)	(0.022)	(0.024)	(0.023)	(0.024)
Ftr. Negative News	-0.007**	-0.006**	-0.005*	-0.004	-0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Log(Number of Picks)	0.001	0.004	0.002	0.003	0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Portfolio Optimism	0.304***	0.316***	0.324***	0.227***	0.235***	0.241***
	(0.026)	(0.023)	(0.020)	(0.030)	(0.028)	(0.027)
Portfolio Ex-market Ret.	-0.024	0.008	0.005	-0.005	-0.010	0.051
	(0.075)	(0.073)	(0.073)	(0.066)	(0.066)	(0.074)
CAPS Consensus	0.295***	0.296***	0.236***	0.272***	0.222***	
	(0.024)	(0.022)	(0.025)	(0.021)	(0.025)	
Log(Market Cap.)	0.003***	0.004***	0.021***	0.006***	0.021***	
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	
Log(Book-to-Market)	-0.001*	-0.002***	-0.000	-0.002***	-0.000	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
CAPM Beta	-0.009***	-0.005**	0.003	-0.005**	0.001	
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
Log(CAPS Age)	-0.002	-0.002	-0.002			
	(0.001)	(0.002)	(0.001)			
Day FE	No	Yes	Yes	Yes	Yes	No
Stock FE	No	No	Yes	No	Yes	No
Forecaster FE	No	No	No	Yes	Yes	Yes
Stock x Month FE	No	No	No	No	No	Yes
Observations	123,117	123,055	122,506	119,268	118,706	84,669
Adj. R-squared	0.590	0.604	0.615	0.674	0.683	0.718

Table A3: Optimism Shifting to Longer Horizons following Negative News — Robustness using $Ret - GSPC$. This table shows the results of estimating Eq. (2) using the negative news measure computed relative to the GSPC index. The details of the estimations are provided under Tables 5. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Longer Horizon	0.081***	0.074***	0.065***	0.086***	0.077***	0.071**
	(0.025)	(0.024)	(0.023)	(0.025)	(0.024)	(0.028)
Past Optimism x Negative News	0.079***	0.074***	0.072***	0.063***	0.062***	0.052***
	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Negative News	-0.124***	-0.127***	-0.121***	-0.110***	-0.105***	-0.066***
	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)	(0.013)
Past Optimism	0.475***	0.463***	0.409***	0.428***	0.375***	0.247***
	(0.033)	(0.032)	(0.028)	(0.039)	(0.034)	(0.030)
Longer Horizon	0.318***	0.315***	0.298***	0.306***	0.287***	0.227***
	(0.025)	(0.024)	(0.021)	(0.029)	(0.025)	(0.027)
Past Optimism x Longer Horizon	-0.315***	-0.305***	-0.283***	-0.289***	-0.267***	-0.196***
	(0.029)	(0.028)	(0.025)	(0.034)	(0.029)	(0.028)
Negative News x Longer Horizon	-0.075***	-0.071***	-0.065***	-0.095***	-0.086***	-0.079***
	(0.024)	(0.022)	(0.021)	(0.023)	(0.022)	(0.025)
Ftr. Negative News	-0.006**	-0.005*	-0.004*	-0.003	-0.002	0.005
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Log(Number of Picks)	0.002	0.004	0.002	0.003	0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)
Portfolio Optimism	0.304***	0.316***	0.324***	0.225***	0.232***	0.238***
	(0.026)	(0.023)	(0.020)	(0.030)	(0.028)	(0.027)
Portfolio Ex-market Ret.	-0.086	-0.011	-0.013	-0.019	-0.023	0.031
	(0.074)	(0.072)	(0.073)	(0.066)	(0.066)	(0.072)
CAPS Consensus	0.296***	0.297***	0.236***	0.273***	0.222***	
	(0.024)	(0.022)	(0.025)	(0.021)	(0.025)	
Log(Market Cap.)	0.003***	0.004***	0.021***	0.007***	0.020***	
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	
Log(Book-to-Market)	-0.001*	-0.002***	-0.000	-0.002***	-0.000	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
CAPM Beta	-0.010***	-0.006**	0.003	-0.005**	0.001	
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	
Log(CAPS Age)	-0.002*	-0.002	-0.002			
	(0.001)	(0.002)	(0.001)			
Day FE	No	Yes	Yes	Yes	Yes	No
Stock FE	No	No	Yes	No	Yes	No
Forecaster FE	No	No	No	Yes	Yes	Yes
Stock x Month FE	No	No	No	No	No	Yes
Observations	123,117	123,055	122,506	119,268	118,706	84,669
Adj. R-squared	0.588	0.603	0.614	0.673	0.683	0.717

Table A4: Optimism Shifting to Longer Horizons following Negative News — Robustness using Raw Stock Returns. This table shows the results of estimating Eq. (2) using the negative news measure based on a stock's raw return. The details of the estimations are provided under Tables 5. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimisim											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Neg News based on Weighted Ret − SPY												
Negative News	-0.162***	-0.167***	-0.155***	-0.160***	-0.134***	-0.155***	-0.142***	-0.134***	-0.123***	-0.130***	-0.073***	-0.117***
	(0.013)	(0.019)	(0.011)	(0.018)	(0.010)	(0.017)	(0.012)	(0.019)	(0.011)	(0.018)	(0.010)	(0.018)
Past Optimism x Negative News		0.102***		0.095***		0.096***		0.069***		0.071***		0.097***
		(0.016)		(0.016)		(0.015)		(0.017)		(0.015)		(0.017)
Past Optimism		0.399***		0.391***		0.338***		0.376***		0.323***		0.185***
		(0.035)		(0.033)		(0.029)		(0.042)		(0.036)		(0.031)
Observations	123,106	123,106	123,044	123,044	122,495	122,495	119,257	119,257	118,695	118,695	83,219	83,219
Adjusted R-squared	0.471	0.579	0.496	0.593	0.536	0.605	0.598	0.667	0.628	0.677	0.695	0.713
Panel B: Neg News based on Weighted Ret − GSPC												
Negative News	-0.162***	-0.168***	-0.155***	-0.161***	-0.134***	-0.156***	-0.142***	-0.134***	-0.123***	-0.131***	-0.072***	-0.116***
	(0.013)	(0.019)	(0.011)	(0.018)	(0.010)	(0.017)	(0.012)	(0.019)	(0.011)	(0.018)	(0.010)	(0.018)
Past Optimism x Negative News		0.103***		0.097***		0.097***		0.071***		0.072***		0.097***
		(0.016)		(0.016)		(0.015)		(0.017)		(0.015)		(0.017)
Past Optimism		0.399***		0.391***		0.338***		0.376***		0.323***		0.185***
		(0.035)		(0.033)		(0.029)		(0.042)		(0.036)		(0.031)
Observations	123,106	123,106	123,044	123,044	122,495	122,495	119,257	119,257	118,695	118,695	83,219	83,219
Adjusted R-squared	0.471	0.579	0.496	0.593	0.536	0.606	0.598	0.667	0.628	0.677	0.695	0.713
Panel C: Neg News based on Weighted Ret												
Negative News	-0.139***	-0.153***	-0.151***	-0.154***	-0.130***	-0.148***	-0.134***	-0.127***	-0.117***	-0.123***	-0.053***	-0.100***
	(0.013)	(0.018)	(0.011)	(0.017)	(0.010)	(0.016)	(0.012)	(0.019)	(0.011)	(0.018)	(0.009)	(0.017)
Past Optimism x Negative News		0.105***		0.093***		0.093***		0.068***		0.070***		0.097***
		(0.017)		(0.016)		(0.015)		(0.018)		(0.015)		(0.018)
Past Optimism		0.405***		0.398***		0.344***		0.382***		0.328***		0.187***
		(0.035)		(0.033)		(0.029)		(0.042)		(0.036)		(0.032)
Observations	123,106	123,106	123,044	123,044	122,495	122,495	119,257	119,257	118,695	118,695	83,219	83,219
Adj. R^2	0.464	0.577	0.493	0.592	0.533	0.604	0.596	0.666	0.626	0.676	0.694	0.713
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Stock FE	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Forecaster FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Stock × Month FE	No	No	No	No	No	No	No	No	No	No	Yes	Yes

Table A5: The Predictive Power of Weighted Return-based Negative News and Conditional Response to News. This table shows the results of regressing a dummy variable for optimism on different negative news indicator variables in the belief-update sample. The optimism dummy variable equals one for predictions that a stock will outperform the market and zero otherwise. The negative news indicator— measured as of $t-1$ where t is the past prediction termination day—equals one if the stock return measure denoted in the panel label is negative and zero otherwise. The construction of the underlying stock returns is described under Table 2. The control variables used in the regression are described under Table 4 in the main text. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism			
	Weighted Ret − SPY	Weighted Ret − GSPC	Weighted Ret	SUE
	(1)	(2)	(3)	(4)
Past Optimism x Negative News x Longer Horizon	0.094***	0.095***	0.078***	0.122***
	(0.026)	(0.026)	(0.026)	(0.033)
Past Optimism x Negative News	0.054***	0.055***	0.055***	-0.005
	(0.016)	(0.016)	(0.016)	(0.010)
Negative News	-0.112***	-0.112***	-0.106***	-0.017**
	(0.019)	(0.019)	(0.018)	(0.008)
Past Optimism	0.375***	0.375***	0.379***	0.419***
	(0.037)	(0.037)	(0.037)	(0.031)
Longer Horizon	0.289***	0.289***	0.284***	0.308***
	(0.028)	(0.028)	(0.028)	(0.028)
Past Optimism x Longer Horizon	-0.275***	-0.275***	-0.266***	-0.293***
	(0.031)	(0.031)	(0.032)	(0.032)
Negative News x Longer Horizon	-0.090***	-0.090***	-0.084***	-0.098***
	(0.026)	(0.026)	(0.025)	(0.030)
Ftr. Negative News	-0.002	-0.002	-0.002	-0.005
	(0.002)	(0.002)	(0.002)	(0.004)
Log(Number of Picks)	0.002	0.003	0.003	0.015*
	(0.005)	(0.005)	(0.005)	(0.008)
Portfolio Optimism	0.232***	0.232***	0.232***	0.249***
	(0.028)	(0.028)	(0.028)	(0.034)
Portfolio Ex-market Ret.	0.014	0.015	0.008	-0.133
	(0.066)	(0.066)	(0.067)	(0.100)
CAPS Consensus	0.224***	0.224***	0.224***	0.263***
	(0.026)	(0.026)	(0.026)	(0.041)
Log(Market Cap.)	0.020***	0.020***	0.020***	0.018***
	(0.003)	(0.003)	(0.003)	(0.004)
Log(Book-to-Market)	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
CAPM Beta	0.002	0.002	0.002	0.000
	(0.002)	(0.002)	(0.002)	(0.005)
Day FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Forecaster FE	Yes	Yes	Yes	Yes
Observations	118,695	118,695	118,695	37,371
Adj. R-squared	0.684	0.684	0.683	0.663

Table A6: Optimism Shifting — Robustness using Weighted Returns and Earnings Surprise. This table shows the results of estimating Eq. (2) using the negative news measures based on a stock's exponentially weighted ex-SPY, ex-GSPC, and raw returns in columns (1) - (3), respectively, and earnings surprise (SUE) in column (4). The details of the estimations are provided under Tables 5, and the construction of the variables is described in Table A1. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism					
	Horizon Change (Years)			Horizon Change (Rank)		
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Horizon Change	0.022***	0.021***	0.019***	0.026***	0.026***	0.023**
	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)
Past Optimism x Negative News	0.095***	0.076***	0.076***	0.096***	0.077***	0.076***
	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)
Negative News	-0.147***	-0.130***	-0.125***	-0.147***	-0.131***	-0.125***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.015)	(0.015)
Past Optimism	0.356***	0.386***	0.334***	0.358***	0.387***	0.336***
	(0.027)	(0.038)	(0.033)	(0.027)	(0.038)	(0.033)
Horizon Change	0.047***	0.045***	0.042***	0.069***	0.065***	0.060***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)
Past Optimism x Horizon Change	-0.012**	-0.015***	-0.013**	-0.004	-0.009	-0.005
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)
Negative News x Horizon Change	-0.010**	-0.011**	-0.010**	-0.012*	-0.014**	-0.012*
	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Ftr. Negative News	-0.005*	-0.004	-0.003	-0.005**	-0.004	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Number of Picks)	-0.002	0.002	0.002	-0.002	0.002	0.002
	(0.002)	(0.005)	(0.005)	(0.002)	(0.005)	(0.005)
Portfolio Optimism	0.341***	0.239***	0.245***	0.339***	0.238***	0.245***
	(0.020)	(0.030)	(0.028)	(0.020)	(0.029)	(0.027)
Portfolio Ex-market Ret.	0.014	0.003	-0.003	0.013	0.002	-0.003
	(0.070)	(0.065)	(0.064)	(0.070)	(0.065)	(0.064)
CAPS Consensus	0.243***	0.275***	0.226***	0.241***	0.274***	0.225***
	(0.026)	(0.021)	(0.026)	(0.025)	(0.021)	(0.026)
Log(Market Cap.)	0.023***	0.007***	0.022***	0.023***	0.007***	0.022***
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
Log(Book-to-Market)	-0.000	-0.002***	-0.000	-0.000	-0.002***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CAPM Beta	0.003	-0.005**	0.001	0.003	-0.005**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(CAPS Age)	-0.002			-0.002		
	(0.001)			(0.001)		
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	No	Yes	Yes	No	Yes
Forecaster FE	No	Yes	Yes	No	Yes	Yes
Observations	122,506	119,268	118,706	122,506	119,268	118,706
Adj. R-squared	0.618	0.675	0.684	0.620	0.677	0.686

Table A7: Optimism Shifting — Robustness to Alternative Horizon Shift Measures. This table shows the results of estimating Eq. (2) using alternative horizon shift measures. In the first set of columns, horizon change is the difference (in years) between the horizons of a forecaster's new prediction and the past prediction being updated. In the second set of columns, horizon change is the difference between the integer ranks of the forecaster's new and past prediction horizons. The ranks range from 1 for the three-week horizon to 5 for the five-year horizon. The details of the estimations are provided under Tables 5. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism											
	$0 \leq \tau \leq 3$						$0 \leq \tau \leq 10$					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Negative News	-0.131***	-0.160***	-0.136***	-0.142***	-0.117***	-0.136***	-0.119***	-0.145***	-0.122***	-0.130***	-0.107***	-0.125***
	(0.009)	(0.014)	(0.011)	(0.016)	(0.009)	(0.015)	(0.007)	(0.012)	(0.009)	(0.013)	(0.008)	(0.013)
Past Optimism x Negative News		0.104***		0.085***		0.086***		0.099***		0.083***		0.082***
		(0.013)		(0.014)		(0.013)		(0.011)		(0.012)		(0.011)
Past Optimism		0.328***		0.370***		0.315***		0.347***		0.370***		0.324***
		(0.029)		(0.042)		(0.036)		(0.024)		(0.033)		(0.028)
Ftr. Negative News	-0.005**	-0.004*	-0.005*	-0.004	-0.003	-0.003	-0.004	-0.004	-0.002	-0.003	-0.001	-0.002
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Log(Number of Picks)	-0.013***	-0.003	-0.006	0.004	-0.005	0.003	-0.015***	-0.004**	-0.011**	-0.002	-0.010**	-0.002
	(0.003)	(0.003)	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)	(0.002)	(0.005)	(0.004)	(0.005)	(0.004)
Portfolio Optimism	0.607***	0.349***	0.481***	0.235***	0.446***	0.242***	0.616***	0.346***	0.453***	0.217***	0.424***	0.224***
	(0.019)	(0.021)	(0.040)	(0.033)	(0.036)	(0.031)	(0.018)	(0.018)	(0.032)	(0.026)	(0.030)	(0.025)
Portfolio Ex-market Ret.	-0.051	-0.041	-0.086	-0.032	-0.072	-0.030	0.047	0.018	-0.049	-0.010	-0.051	-0.018
	(0.091)	(0.077)	(0.079)	(0.073)	(0.074)	(0.071)	(0.073)	(0.057)	(0.060)	(0.052)	(0.057)	(0.051)
CAPS Consensus	0.531***	0.253***	0.520***	0.283***	0.464***	0.237***	0.551***	0.254***	0.535***	0.289***	0.483***	0.243***
	(0.045)	(0.027)	(0.038)	(0.022)	(0.049)	(0.027)	(0.040)	(0.023)	(0.035)	(0.020)	(0.041)	(0.023)
Log(Market Cap.)	0.036***	0.024***	0.012***	0.007***	0.033***	0.023***	0.037***	0.024***	0.010***	0.007***	0.033***	0.023***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)
Log(Book-to-Market)	-0.001	-0.001	-0.004***	-0.002***	-0.001	-0.001	-0.000	0.000	-0.003***	-0.001***	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CAPM Beta	0.003	0.003	-0.009***	-0.005**	0.000	0.001	0.002	0.002	-0.008***	-0.004**	0.001	0.001
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Log(CAPS Age)	-0.004	-0.002					-0.003	-0.002				
	(0.002)	(0.001)					(0.002)	(0.001)				
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Forecaster FE	No	No	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Observations	105,824	105,824	102,920	102,920	102,333	102,333	155,713	155,713	151,797	151,797	151,275	151,275
Adj. R-squared	0.549	0.616	0.613	0.682	0.644	0.692	0.509	0.587	0.567	0.641	0.595	0.650

Table A8: Conditional Response to News — Robustness to Alternative Belief-update Event Definitions. This table shows the results of regressing a dummy variable for optimism on the ex-SPY return-based negative news indicator variable in the belief-update sample using alternative restrictions on the number of days, τ, between a forecaster's termination of a prediction and initiation of another one on the same stock. In the first set of columns, the belief update event must occur within three days ($0 \leq \tau \leq 3$), that is, when a forecaster ends a prediction, the new prediction must be initiated within three days. In the second set of columns, the belief update event must occur within 10 days ($0 \leq \tau \leq 10$). The optimism dummy variable equals one for predictions that a stock will outperform the market and zero otherwise. The negative news indicator—measured as of $t-1$ where t is the past prediction termination day—equals one if the ex-SPY stock return measure is negative and zero otherwise. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism					
	$0 \leq \tau \leq 3$			$0 \leq \tau \leq 10$		
	(1)	(2)	(3)	(4)	(5)	(6)
Past Optimism x Negative News x Longer Horizon	0.075***	0.100***	0.091***	0.052**	0.067***	0.062***
	(0.025)	(0.027)	(0.026)	(0.021)	(0.023)	(0.022)
Past Optimism x Negative News	0.079***	0.068***	0.069***	0.078***	0.069***	0.069***
	(0.013)	(0.014)	(0.014)	(0.011)	(0.012)	(0.011)
Negative News	-0.136***	-0.123***	-0.119***	-0.124***	-0.114***	-0.110***
	(0.015)	(0.017)	(0.016)	(0.013)	(0.014)	(0.014)
Past Optimism	0.395***	0.423***	0.367***	0.411***	0.422***	0.375***
	(0.031)	(0.043)	(0.037)	(0.025)	(0.034)	(0.030)
Longer Horizon	0.296***	0.308***	0.287***	0.288***	0.294***	0.278***
	(0.023)	(0.032)	(0.028)	(0.020)	(0.026)	(0.024)
Past Optimism x Longer Horizon	-0.288***	-0.299***	-0.275***	-0.273***	-0.275***	-0.257***
	(0.027)	(0.037)	(0.032)	(0.023)	(0.030)	(0.026)
Negative News x Longer Horizon	-0.060**	-0.097***	-0.087***	-0.051***	-0.074***	-0.067***
	(0.024)	(0.026)	(0.025)	(0.020)	(0.021)	(0.021)
Ftr. Negative News	-0.005**	-0.004*	-0.003	-0.005	-0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Log(Number of Picks)	0.002	0.007	0.006	0.000	0.001	0.000
	(0.003)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)
Portfolio Optimism	0.322***	0.220***	0.228***	0.319***	0.203***	0.211***
	(0.021)	(0.032)	(0.030)	(0.018)	(0.025)	(0.024)
Portfolio Ex-market Ret.	-0.053	-0.043	-0.039	0.019	-0.012	-0.020
	(0.079)	(0.073)	(0.072)	(0.058)	(0.051)	(0.050)
CAPS Consensus	0.238***	0.272***	0.224***	0.239***	0.278***	0.232***
	(0.026)	(0.022)	(0.026)	(0.022)	(0.019)	(0.022)
Log(Market Cap.)	0.022***	0.007***	0.022***	0.022***	0.006***	0.021***
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
Log(Book-to-Market)	-0.001	-0.002***	-0.001	0.000	-0.001***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
CAPM Beta	0.003	-0.005**	0.001	0.002	-0.004**	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(CAPS Age)	-0.002			-0.002		
	(0.001)			(0.001)		
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	No	Yes	Yes	No	Yes
Forecaster FE	No	Yes	Yes	No	Yes	Yes
Observations	105,824	102,920	102,333	155,713	151,797	151,275
Adj. R-squared	0.625	0.689	0.698	0.597	0.649	0.657

Table A9: Optimism Shifting — Robustness to Alternative Belief-update Event Definition. This table shows the results of estimating Eq. (2) using alternative restrictions on the number of days, τ, between a forecaster's termination of a prediction and initiation of another one on the same stock. In the first set of columns, the belief update event must occur within three days ($0 \leq \tau \leq 3$), that is, when a forecaster ends a prediction, the new prediction must be initiated within three days. In the second set of columns, the belief update event must occur within 10 days ($0 \leq \tau \leq 10$). The details of the estimations are provided under Tables 5. Standard errors, in parentheses, are clustered at the forecaster and day levels.

	Future Optimism									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: 1 year gap and 200 dictionary terms										
Negative News	-0.025***	-0.009	-0.031***	-0.016**	-0.032***	-0.016**	-0.031***	-0.016**	-0.032***	-0.016**
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News	0.013**	-0.005	0.015***	-0.002	0.017***	-0.001	0.017***	-0.001	0.019***	0.002
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)
Past Optimism x Negative News x Higher Horizon Lang.		0.036***		0.034***		0.036***		0.034***		0.035***
		(0.010)		(0.010)		(0.010)		(0.010)		(0.011)
Observations	102451	102451	102150	102150	101419	101419	100943	100943	100199	100199
Adj. R^2	0.359	0.359	0.371	0.371	0.385	0.386	0.387	0.387	0.404	0.404
Panel B: 1 year gap and 100 dictionary terms										
Negative News	-0.025***	-0.012*	-0.031***	-0.020***	-0.032***	-0.020***	-0.031***	-0.020***	-0.032***	-0.020***
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News	0.013**	-0.002	0.015***	0.001	0.017***	0.002	0.017***	0.003	0.019***	0.004
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.008)
Past Optimism x Negative News x Higher Horizon Lang.		0.030***		0.027***		0.029***		0.028***		0.030***
		(0.010)		(0.010)		(0.010)		(0.010)		(0.011)
Observations	102451	102451	102150	102150	101419	101419	100943	100943	100199	100199
Adj R-squared	0.359	0.359	0.371	0.371	0.385	0.386	0.387	0.387	0.404	0.404
Panel C: 3 year gap and 200 dictionary terms										
Negative News	-0.024***	-0.009	-0.030***	-0.015**	-0.031***	-0.015**	-0.030***	-0.014**	-0.030***	-0.014**
	(0.004)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News	0.012**	-0.006	0.013***	-0.005	0.016***	-0.003	0.014***	-0.004	0.017***	-0.002
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News x Higher Horizon Lang.		0.036***		0.035***		0.037***		0.038***		0.038***
		(0.010)		(0.010)		(0.010)		(0.010)		(0.010)
Observations	113142	113142	112855	112855	112145	112145	111604	111604	110898	110898
Adjusted R-squared	0.343	0.343	0.355	0.356	0.371	0.371	0.373	0.374	0.391	0.392
Panel D: 3 year gap and 100 dictionary terms										
Negative News	-0.024***	-0.012*	-0.030***	-0.019***	-0.031***	-0.020***	-0.030***	-0.017**	-0.030***	-0.018***
	(0.004)	(0.006)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News	0.012**	-0.003	0.013***	-0.001	0.016***	0.001	0.014***	-0.002	0.017***	0.002
	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)
Past Optimism x Negative News x Higher Horizon Lang.		0.029***		0.028***		0.029***		0.032***		0.031***
		(0.010)		(0.010)		(0.010)		(0.010)		(0.010)
Observations	113142	113142	112855	112855	112145	112145	111604	111604	110898	110898
Adjusted R-squared	0.343	0.343	0.355	0.355	0.371	0.371	0.373	0.374	0.391	0.391
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	No	No	No	No	Yes	Yes	No	No	Yes	Yes
User FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Table A10: Optimism Shifting Evidence based on Seeking Alpha Posts. This table shows the results for the panel regression of user i's $Optimism$ about stock k on day t on the triple interaction term *Past Optimism* $\times$ *Negative News* $\times$ *Higher Horizon Language* using articles posted by individuals on Seeking Alpha (SA). $Optimism$ (*Past Optimism*) is a dummy variable that equals one if the user's current (prior) view on stock k is bullish. *Negative News* is a dummy variable that equals one if stock k's on-week return ending $t-2$ is negative. *Higher Horizon Language* is a dummy variable that equals one if the user's current view on stock k loads more on our long-term lexicon than their past view on the stock. We require at least ten days between a user's prior and current post on a stock. As the panel labels indicate, we require either a maximum of one- or three-year gap between a user's prior and current post on a stock and quantify an article's long-term thinking using either 200 or 100 long-term lexicon terms. All specifications include the following control variables: the individual and two-way interaction terms, user average optimism over the past six months, user log number of posts over the past six months, log user age on SA, stock average optimism on SA over the past six months, log stock market cap., log book-to-market ratio, and CAPM beta. Standard errors, in parentheses, are clustered at the user and day levels.