Earnings Calls and Echo Chambers:
Evidence from the Introduction of Livestreaming on StockTwits

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Abstract

We examine whether improved access to firm disclosures weakens social media echo chambers, using the introduction of livestreamed earnings calls on StockTwits as a shock. We find that call streaming is associated with lower selective following, reduced exposure to confirmatory content, and belief revision over the following 30 days. Both call content and real-time chats contribute, with the strongest effects when calls surface disconfirming information and chats are active and diverse. The findings suggest that reducing frictions to accessing primary information and increasing exposure to diverse views can help mitigate the consequences of echo chambers in financial markets.

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1. Introduction

Information consumption is becoming increasingly concentrated, with individuals relying on a narrower set of sources and often turning to social media sources over traditional outlets.[1] These shifts have fostered information echo chambers, which have been shown to affect political discourse, perceptions of climate change, and public health campaigns (e.g., Hobolt et al., 2024; Bowen, Dmitriev, and Galperti, 2023; Allcott et al., 2020b). Cookson, Engelberg, and Mullins (2023) find that this phenomenon extends to financial markets. Despite investors' clear incentives to seek out value-relevant information, they tend to gravitate toward others with similar views, which leads to polarized information exposure and worse investment outcomes.

Explanations for echo chambers emphasize behavioral underpinnings such as confirmation bias (e.g., Faia et al., 2024), information avoidance (e.g., Andries and Haddad, 2020), and motivated beliefs (e.g., Banerjee, Davis, and Gondhi, 2024). Consistent with these mechanisms, evidence from political settings shows that altering information exposure, by changing news sources (e.g., Levy, 2021) or social contacts (e.g., Allcott et al., 2020a), can reduce polarization. Notably, Cookson, Engelberg, and Mullins (2023) find that earnings releases exacerbate financial echo chambers, suggesting that public information can increase polarization.

The failure of primary firm disclosures to weaken echo chambers is striking, especially considering a regulatory system that requires firms to provide equal access to information that is relevant, neutral, and complete. We hypothesize that information frictions may hinder corporate disclosures from effectively reducing echo chambers in capital markets. When accessing primary information sources is relatively costly, investors may rely on third-party commentaries or social reactions that reinforce existing views and amplify belief divergence between groups.

[1] For example, Shearer et al. (2025) finds that 57% of Republicans obtain their news from a single source, while Stocking et al. (2024) reports that 54% of US adults receive news from social media.

In this article, we exploit the 2024 introduction of livestreamed earnings calls into the StockTwits platform to examine how shocks to information flows affect financial echo chambers. Access to streamed calls altered users' information environment in two important ways. First, by embedding calls directly within the StockTwits interface (without requiring separate logins or navigation to external sites), the platform reduced friction costs associated with accessing primary firm disclosures. Second, the inclusion of a dedicated, call-specific chat created a synchronous social context where users react to the disclosure together. Unlike the main curated feed, which elevates posts from followed users, the earnings-call chat occupies a separate space that makes counter-attitudinal comments more visible than in their personalized feed.

We start by documenting that streaming meaningfully altered user behavior along multiple dimensions. Specifically, we find that streamed calls are associated with 73 percent higher firm pageviews and 66 percent more messages about the focal firm relative to non-streamed calls. These increases are substantial, given that earnings calls were already publicly available elsewhere. The evidence indicates that embedding disclosure within an interactive social context meaningfully affects how investors engage with corporate information.

More importantly, we find that earnings call streaming is associated with reduced echo chamber formation. Consistent with Cookson, Engelberg, and Mullins (2023), we confirm the baseline echo chamber result that users declaring bullish sentiment in the ten days before an earnings announcement are significantly more likely to follow other bullish users in the subsequent days. However, when the earnings call is streamed on StockTwits, this selective following behavior is reduced by approximately 61 percent relative to non-streamed calls.

The effect of streamed earnings calls extends beyond the decision to follow other like-minded users. We observe that bullish users exposed to streamed calls also exhibit significantly lower consumption of bullish content, as measured by impressions from followed users, and reduced engagement with bullish messages, as measured by likes. These patterns indicate a substantial disruption of the echo chamber mechanisms documented in prior work.

We also find evidence that the behavioral changes associated with streamed earnings calls translate into revisions in beliefs and shifts in trading behavior. In particular, bullish users exposed to streamed calls produce significantly fewer net-bullish posts in the 30 days following the call, with the effect strengthening over time. In addition, documented bulls are less likely to purchase the stock after streamed calls, as signaled by buy declarations. The pattern is consistent with gradual belief revision rather than a temporary reaction.

To understand the mechanisms underlying these effects, we examine heterogeneity in both the earnings calls themselves and the accompanying chat discussions. We find that the quality and content of the earnings call itself significantly moderates the treatment effect. Effects are stronger when calls feature high interactivity, measured by the number of question-and-answer exchanges between analysts and management, suggesting that dynamic dialogue revealing management's responses is more effective than passive presentations. We also find stronger effects when analyst questions or management responses convey more negative or cautious tones and when management uses clearer, less obfuscated language. These patterns suggest that calls are most effective at breaking echo chambers when they surface disconfirming information through interactive dialogue and clear language, supporting the hypothesis that access to unfiltered disclosure plays a central role.

Contemporaneous chat characteristics also moderate the treatment effect. Effects are strongest when chats are highly active and include a greater share of bearish participants, exposing bullish users to counter-attitudinal views in real-time. The content of the discussion matters as well: longer messages, specific references to numbers or events, and broader thematic coverage all amplify the effect. While superficial commentary appears to have limited impact, substantive engagement with disconfirming perspectives is associated with weakened echo chambers.

Taken together, the findings suggest that reducing frictions associated with accessing primary information and exposing users to how others with different views interpret the same news can weaken the formation of information echo chambers. Moreover, the evidence that streaming is most impactful when disclosures are disconfirming, clear, and interactive, and when chats are substantive, suggests that echo chambers are most fragile to information that challenges prior narratives, leaves little room for alternative interpretations, and is vetted in real time by experts and a broad set of social media users.

Our study contributes to the growing literature on social finance.[2] Past work documents that financial social media conveys value-relevant information, informs corporate decisions, affects professional forecasts, and can impact capital markets (e.g., Chen et al., 2014; Blankespoor, Miller, and White, 2014; Bartov, Faurel, and Mohanram, 2018; Campbell, D'Adduzio, and Moon, 2023; Booker, Curtis, and Richardson, 2023; Cookson, Lu, Mullins, and Niessner, 2024; Cookson, Niessner, and Schiller, 2024; Dessaint, Foucault, and Frésard, 2024).

More closely related is the literature that focuses on how social networks influence the diffusion of information and shape behavior (e.g., Hirshleifer, 2020; Han, Hirshleifer, and Walden, 2022, 2023). Existing work shows that disagreement can persist even around public information releases, with investors who receive the same earnings news interpreting it differently depending on their social connections (Giannini, Irvine, and Shu, 2019; Cookson and

[2] Kuchler and Stroebel (2021) and Cookson, Mullins, and Niessner (2024) survey the literature.

Niessner, 2020). Cookson, Engelberg, and Mullins (2023) finds that firm disclosures can amplify polarization, as investors follow like-minded peers and consume more confirming content after earnings events. Hirshleifer, Peng, and Wang (2025) show that social connections accelerate news diffusion within groups, but also sustain disagreement across groups. Our analysis indicates that streaming firm news directly into the social-media environment reduces echo chambers by lowering the frictions that limit how public information is accessed and interpreted. The evidence that streaming is more impactful when event chats are active and sentimentally diverse is consistent with the idea that weakening network segmentation can reduce echo chambers. The findings highlight how call streaming expands the reach of public signals and alters the context in which they are interpreted, shedding light on when value-relevant information can overcome selective exposure and motivated reasoning in social networks.

The findings also contribute broadly to the literature on corporate disclosure by showing that the impact of earnings calls depends not only on what firms choose to reveal but also on the information venue. Existing work shows that the informativeness of earnings calls varies with their content, including the relative emphasis on scripted presentations versus Q&A, the presence of deceptive or complex language, extreme wording, and conversational engagement (e.g., Matsumoto, Pronk, and Roelofsen, 2011; Larcker and Zakolyukina, 2012; Huang, Teoh, and Zhang, 2014; Lee, 2016; Bushee, Gow, and Taylor, 2018; Cohen, Lou, and Malloy, 2020; Bochkay, Hales, and Chava, 2020; Gow, Larcker, and Zakolyukina, 2021; Rennekamp, Sethuraman, and Steenhoven, 2022). Our evidence that the effects of streaming are stronger when calls feature more Q&A, clearer language, or more disconfirming content suggests that disclosure has a greater impact on investor beliefs when it is embedded in a synchronous interactive platform.

2. Data and Sample

2.1.Conference Call Livestreams on StockTwits

StockTwits is a social networking platform designed for investors to share opinions about securities. Founded in 2008, the platform has grown to become one of the largest financial social media networks, with 3.5 million users comprising a cross-section of market participants ranging from retail investors to finance professionals. The platform's interface uses "cashtags" that place a dollar sign before a security's ticker symbol (e.g., $AAPL for Apple or $TSLA for Tesla), which allows users to aggregate discussions about specific securities.

A key feature of StockTwits is its sentiment-tagging system. When posting a message, users can mark their sentiment as *bullish* or *bearish* by clicking an icon. This self-declared sentiment is visible to other users and serves as a signal of the poster's view. Prior research validates that StockTwits sentiment and attention measures contain information relevant for asset pricing (Cookson and Niessner, 2020) and that users can interpret management disclosures in real time (Campbell, D'Adduzio, and Moon, 2023).

The platform's social network structure allows users to follow others, creating personalized newsfeeds. When user A follows user B, all of B's future messages automatically appear in A's newsfeed. This architecture creates the potential for echo chambers: if users selectively follow like-minded individuals, their newsfeeds become increasingly homogeneous in sentiment. Cookson, Engelberg, and Mullins (2023) document that self-described bulls are five times more likely to follow other bulls than bears, leading to persistent information segmentation.

In July 2024, StockTwits introduced a feature allowing users to stream corporate earnings conference calls directly within the platform. This feature represented a departure from the typical information environment, where users encounter earnings information through post-call summaries, news articles, or delayed peer commentary.

Each streamed call is presented on a dedicated page with three tabs. We provide an example of this layout in Appendix A. The Chat tab hosts a real-time discussion forum specific to the earnings call. Users can post messages beginning one hour before the call starts, continuing throughout the call, and extending one hour after the call ends. This chat is temporally and topically distinct from the general message stream about the company: it exists only for the specific earnings event and closes two hours after the call ends.

The Data tab displays summary financial information, including consensus earnings per share estimates, revenue forecasts, analyst ratings, recent price movements, and excerpts from the firm's 8-K filing. The tab also provides direct links to the full 8-K on the SEC's EDGAR database and to the company's investor relations page. The Transcript tab provides a continuously updated transcript of the earnings call audio. As management speaks or analysts ask questions, the transcript updates in real time, allowing users to read along while listening or to scan back through earlier portions of the call.

The feature was rolled out gradually across firms and time. StockTwits began with a pilot phase in Q2 2024, streaming 12 calls for selected large-cap technology firms. According to discussions with the platform, these initial selections reflected internal testing of new livestreaming capabilities rather than firm-specific news considerations. Coverage expanded substantially in Q3 2024 and remained at similar levels through Q4 2024.

2.2. Sample Construction

Our main sample comprises all Compustat firm-quarters in 2024 with a non-missing earnings announcement date that we can match to StockTwits via GVKEY. For these firms, we identify all earnings calls streamed on StockTwits between July and December 2024. For each streamed call, we collect the full chat history and associated metadata, including user identifiers, message text, and timestamps. Around each earnings announcement (from 10 days before to 30 days after), we gather all firm-specific user engagement on StockTwits using the associated cashtag, which allows us to measure bullish and bearish declarations, message volume, pageviews, and user characteristics via the associated metadata.

We merge the StockTwits data with several financial databases. From CRSP, we obtain stock prices, returns, and trading volume. From Compustat, we collect firm characteristics such as market capitalization, book-to-market ratios, profitability, and leverage. From I/B/E/S, we obtain analyst forecasts to compute analyst coverage and earnings surprises. From Thomson Reuters 13F, we measure institutional ownership. From TAQ, we classify trades as retail or institutional, following Boehmer et al. (2021), based on trade size. From Capital IQ, accessed through WRDS, we obtain structured earnings conference call transcripts, which we use to construct measures of call interactivity, sentiment, and linguistic characteristics.

To construct the control group, we identify all 2024 earnings announcements in our sample, but whose calls were not streamed. If a call is unstreamed, we assume a call took place but was not broadcast on the platform. For our main tests, we require only that the firm has an earnings announcement date, a valid StockTwits match, and at least one user sentiment declaration in the 10 days preceding the earnings announcement. We apply additional filters in subsequent analyses as dictated by data availability. Table IA1 in the Internet Appendix lists the sample filters and the resulting number of observations.

We provide an overview of our sample in Table 1. Our final sample contains 6,360 firm-quarter observations, of which 1,188 had their earnings calls livestreamed on StockTwits. The remaining 5,172 firm-quarters serve as controls. The main sample spans 2,968 unique firms and 16,555 users.

2.3 Identifying User Sentiment Declarations

Our empirical strategy requires classifying users' ex-ante beliefs about firms before earnings announcements. We use the sentiment-tagging feature described in Section 2.1 to construct these classifications at the user-firm-day level. For each user i and firm s, we examine all messages posted about firm s during the 10-day window prior to the earnings announcement (days t-10 through t-1, where t is the announcement day). Following Cookson, Engelberg, and Mullins (2023), we classify a user as declaring bullish sentiment (*Declared Bull* = 1) if more than 50 percent of their messages about firm s during this window are marked as bullish.[3] Similarly, we classify a user as declaring bearish sentiment (*Declared Bear* = 1) if more than 50 percent of their messages are marked as bearish. Users who do not post about the firm or primarily post neutral messages are not classified.

Our final sample of user declarations includes 84,157 user-firm-announcement observations. Of these, 75,115 (89.3%) are bullish declarations and 9,042 (10.7%) are bearish declarations. Additional descriptive statistics are presented in Table IA2 in the internet appendix. The higher proportion of bullish declarations is consistent with prior research documenting an optimistic bias on StockTwits (Cookson, Engelberg, and Mullins, 2023) and reflects the asymmetry in investor position-taking, where long positions are more common than short positions in equity markets.

3. Empirical Design and Results

[3] We also consider a 90% threshold for robustness.

3.1 Determinants of Call Streaming

We begin by examining which firms' earnings calls were selected for livestreaming. Understanding this selection is important for two reasons. First, it informs our identification strategy by revealing whether treatment is plausibly exogenous conditional on observables. Second, it provides context for interpreting the results and assessing external validity.

In constructing the echo chamber sample, our main binding restriction is that at least one StockTwits user declares a bullish or bearish view on the stock in the ten days before the earnings announcement. This requirement selects firms with a minimum level of engagement on the platform, which generally corresponds to StockTwits' discussed criteria for inclusion in the initial streaming testing phase.

Focusing on the last two quarters of 2024 when StockTwits began testing, we observe that 3,150 earnings calls satisfy our user engagement filter. Of these calls, 201 are associated with firms that streamed only in Q3, 288 with firms that streamed only in Q4, 692 with firms that streamed in both Q3 and Q4, and 1,969 with firms that did not stream in either quarter. Anecdotally, the fact that some prominent firms, such as Apple, are streamed in Q3 but not Q4 illustrates that streaming is not deterministically tied to firm size or popularity. Conversations with StockTwits indicate that the rollout involved experimentation and capacity constraints with some aspects of A/B testing. Although we do not view the selection process as purely random, the staggered and incomplete rollout for firms that meet an engagement threshold indicates that, after conditioning on observables, the remaining variation in streaming status contains an idiosyncratic component that is useful for identification.

In order to examine whether streaming status is associated with firm characteristics, we estimate a linear probability model where the dependent variable is an indicator equal to one if firm s's earnings call in quarter q was streamed on StockTwits:

$$Streamed_{s,q} = \beta X_{s,q} + \alpha_s + \gamma_q + \varepsilon_{s,q} \quad (1)$$

where $X_{s,q}$ represents a standard set of firm characteristics: *Age*, *Size*, *Market-to-Book*, *ROA*, *Leverage*, *Revenue Growth*, *Price* level, *Turnover*, recent *Return*, *Return Volatility*, *Institutional Ownership*, *Analyst Following*, *Earnings Surprise*, *Retail Trading* share, and StockTwits activity measures (average *Posts*, *Pageviews*, and *Sentiment*). α_s are firm fixed effects, γ_q are year-quarter fixed effects, and standard errors are clustered at the firm level. Again, we restrict the analysis to the third and fourth quarters of 2024, the periods when the decision to stream was most relevant.

Table 2 reports the results. Column 1 presents the main specification, and Column 2 adds year-quarter fixed effects, which account for the gradual rollout of streaming over 2024. Across specifications, we find limited predictability of streaming decisions. Analyst following loads positively, perhaps because StockTwits would like to provide users with a consensus analyst forecast prior to the earnings call. Lagged returns load positively, and return volatility loads negatively. No other firm characteristic is significant, including firm age, size, market-to-book ratio, revenue growth, liquidity, stock price, turnover, recent returns, return volatility, institutional ownership, earnings surprise, retail trading share, or measures of StockTwits user engagement. The evidence supports the view that the decision to stream, once conditioning on a minimum level of platform engagement, has a random component.

In Column 3, we add firm fixed effects. In principle, these absorb time-invariant firm characteristics such as industry, baseline StockTwits popularity, and typical disclosure practices. In practice, since 63% of the call sample is never streamed, the firm fixed effects capture much of the variation in the Streamed indicator. Again, few other characteristics explain the decision to stream. Together, we interpret the evidence of limited predictability in Table 2 as suggesting that after controlling for observable factors and fixed effects, the remaining variation in streaming status exhibits quasi-random idiosyncratic variation that supports our identification strategy.

3.2 Conference Call Streaming and Platform Engagement

Before examining our main research question about echo chambers, we first establish the extent to which call streaming meaningfully alters user engagement with the platform. If investors ignore the feature or already access call information through other channels, we would not expect downstream effects on information networks or beliefs.

We construct an hourly panel at the firm-hour level for the hours surrounding earnings announcements and estimate a difference-in-differences specification that compares engagement during the call hour for streamed versus non-streamed calls:

$$Engagement_{s,h} = \beta_1 CallHour_{s,h} + \beta_2 CallHour_{s,h} \times Streamed_s + \alpha_{s,h} + \gamma_d + \varepsilon_{s,h} \quad (2)$$

where $Engagement_{s,h}$ is an engagement measure (log pageviews, log unique visitors, log messages, or log unique posters) for firm *s* during hour h, $CallHour_{s,h}$ is an indicator equal to one during the hour when the earnings call occurs, and $Streamed_s$ indicates whether the call was streamed on StockTwits. We include two hourly observations for each call, the one-hour period immediately prior to the call, and the first hour of the call.[4] $\alpha_{s,h}$ denotes firm-by-quarter fixed effects, γ_d are date fixed effects, and standard errors are clustered at the firm level.

[4] For the echo chamber analysis, we examine users with sentiment declarations in the ten days prior to the call and track their usage in the month after the call. Thus, the precise (hourly) timing of the call is less important. However, for the engagement analysis, we consider a broader set of users, including those without declared sentiments, and measure activity in the hours immediately around the call, which makes precise timing essential. We therefore require call-time information either through StockTwits or Capital IQ, which reduces the number of earnings observations by roughly 25%. In Table IA3, we confirm that the echo chamber results continue to hold in this smaller sample.

The coefficient β_1 captures the baseline increase in engagement during the call hour (relative to the hour prior to the call) for non-streamed calls, reflecting the typical attention spike when earnings information is released. The coefficient β_2 measures the additional engagement boost when the call is streamed on StockTwits, identifying the causal effect of streaming by comparing the call-hour spike for streamed versus non-streamed calls within the same firm-quarter and on the same date.

Table 3 reports the results. Column 1 examines pageviews. Even non-streamed calls generate a considerable increase in firm-specific pageviews during the call hour, as users seek out earnings information. When calls are streamed, pageviews increase by an additional 68 log points, nearly doubling the baseline engagement. Column 2 examines unique visitors and finds a similar pattern: streaming generates an additional 61 log points increase beyond the baseline effect. The fact that both total pageviews and unique visitors increase substantially suggests that streaming draws a broader cross-section of users to the firm's page rather than simply increasing repeat visits by already-engaged users.

Columns 3 and 4 examine active participation through message production. Specifically, Column 3 shows that streaming increases total messages by an additional 70 log points during the call hour, essentially doubling message activity. Column 4 shows that unique message posters increase by an additional 55 log points. The parallel increases in both message volume and unique posters confirm that streaming generates genuine expansion in participation rather than simply encouraging already-active users to post more frequently. The near-doubling of message activity when calls are streamed indicates substantial engagement with the chat feature.

These engagement results validate that the streaming treatment is relevant and substantial. Users respond by dramatically increasing their attention to and participation in earnings-related content during the call hour. The increases are striking given that earnings calls were already publicly available through other channels such as company investor relations websites, financial news platforms, and audio webcasting services. The fact that embedding calls directly within the StockTwits interface generates such large increases in engagement suggests that the convenience and social context provided by the platform meaningfully lowers barriers to accessing and discussing primary corporate disclosures.

3.3 Conference Call Streaming and Echo Chamber Formation

Having validated that streaming altered user engagement, we turn to our central research question: Does streaming influence echo chamber formation? Following Cookson, Engelberg, and Mullins (2023), we measure echo chamber behavior through users' following decisions. If users selectively follow others with similar views, their newsfeeds become increasingly homogeneous over time, limiting exposure to disconfirming information.

Our dependent variable, $Net\ Follow\ Bull_{i,s,[t,t+9]}$, is an indicator equal to one if user i's net following actions regarding firm *s* in days [*t*, *t*+9] favor bullish users over bearish users. Formally, $Net\ Follow\ Bull_{i,s,[t,t+9]}$ is equal to 1 if (bulls followed – bulls unfollowed) > (bears followed – bears unfollowed), and zero otherwise.[5] We classify the users that user *i* follows based on those users' declarations about firm *s* at the time of the following action, using the 50 percent threshold described in Section 2.3. As in Cookson, Engelberg, and Mullins (2023), the 10-day window allows sufficient time for users to discover new voices through call-related discussion while remaining close enough to the event to plausibly attribute behavior to the call.

We estimate the following specification:

[5] For morning announcers, we treat the announcement day as day *t*; for afternoon announcers, the next day is day *t*.

$$Net\ Follow\ Bull_{i,s,[t,t+9]} = \beta_1 DeclareBull_{i,s,t} + \beta_2 DeclareBull_{i,s,t} \times Streamed_{s,t} + \lambda_i + \alpha_s + \gamma_t + \varepsilon_{i,s,t} \tag{3}$$

where $DeclareBull_{i,s,t}$ equals one if user i expressed bullish sentiment about firm s in days [-10,-1] prior to the earnings announcement date, $Streamed_{s,t}$ indicates whether firm s's call was streamed on day t, λ_i are user fixed effects, α_s are firm fixed effects, and γ_t are date fixed effects. Standard errors are clustered at the user level. The coefficient β_1 captures the baseline tendency for bulls to follow other bulls versus bears, representing the echo chamber effect. The coefficient β_2 measures whether streaming reduces this selective following. Our preferred specification replaces firm and date fixed effects with firm-by-date fixed effects $\alpha_{s,t}$. This more demanding specification absorbs all firm-date-level variation, including any time-varying firm characteristics or news shocks that might correlate with both streaming and user behavior. Identification comes therefore solely from comparing bullish versus bearish users' following behavior within the same firm-quarter.

Table 4 presents the results. Column 1 includes user, firm, and date fixed effects separately. Consistent with Cookson, Engelberg, and Mullins (2023), we find strong evidence of echo chamber behavior: bullish users are significantly more likely to follow other bullish users than bearish users in the 10 days following an earnings announcement. The interaction coefficient indicates that streaming significantly reduces this selective following behavior, cutting the echo chamber effect by approximately half.

Column 2 presents the most conservative specification with firm-by-date fixed effects. The baseline echo chamber effect remains strong and statistically significant. The interaction coefficient strengthens and indicates that streaming reduces selective following behavior by approximately 61 percent. This large reduction suggests that exposure to streamed calls substantially disrupts the echo chamber formation documented in prior work. The stronger effect in column 2 compared to column 1 indicates that controlling flexibly for firm-quarter variation is important, as it accounts for any time-varying firm characteristics or news shocks that might independently affect both streaming decisions and user behavior.

We conduct several robustness checks on the baseline echo-chamber results. We first restrict the sample to users whose pre-announcement messages are more than 90 percent bullish (compared to the baseline 50%), so the classification captures more strongly held views. We next limit the sample to users who were logged into StockTwits during the call window, strengthening identification by requiring users to have direct access to the call stream, rather than indirectly through their feed. We then restrict the sample to firms with precisely timed call transcripts from StockTwits or Capital IQ.[6] We also consider the 2024Q2–Q3 period exclusively, focusing on the quarters immediately before and during the initial streamed calls. Across these variants, tabulated in Table IA3, the interaction between *Declared Bull* and *Streamed* remains significantly negative and of similar magnitude, suggesting that our findings are not driven by particular filtering choices.

Figure 1 provides visual evidence of the effects by plotting cumulative net following over 50 days after the earnings announcement. The solid line representing bulls at non-streamed firms shows a steady accumulation of new follows of other bullish users, rising to approximately 0.25 net new bull follows over the 50-day window. The corresponding line for streamed calls rises much more slowly, accumulating only 0.10 net new bull follows, a 60 percent reduction consistent with the regression estimates.

[6] We do observe calls streamed on StockTwits that do not have transcripts in Capital IQ, indicating that Capital IQ coverage is not complete. Our working assumption for the baseline results is that all firms that meet our filters have conference calls near the earnings announcement in 2024.

Figure IA1 shows the same plot for net bearish following. The dashed lines representing the following of bearish users remain flat near zero for both groups, indicating that bulls rarely follow bears regardless of streaming status. Column 5 in Table IA3 replicates the baseline results for net bearish followers and documents insignificant effects of streaming. The non-results for bearish users indicate that the echo chamber disruption we document operates primarily through bullish investors, who comprise the majority of the platform and have more opportunities for same-sentiment following.

Together, the evidence suggests that streaming has important effects on echo chamber formation. Specifically, bulls exposed to streamed calls are substantially less likely to selectively follow like-minded individuals, suggesting that the treatment alters how users construct their information networks. The observed change in information networks sets the stage for examining whether it translates into changes in information consumption, the focus of the next section.

3.4 Echo Chambers and Information Consumption

The results in Section 3.3 support the view that streaming reduces selective following: bullish users exposed to streamed calls are less likely to follow other bullish users compared to bullish users at non-streamed firms. However, following decisions are merely an input into users' information environments. The question remains whether these changes in network structure translate into meaningful changes in the content users actually see and engage with on the platform.

This distinction matters because users might follow fewer like-minded individuals yet still encounter predominantly confirming content if, for example, the users they do follow post disproportionately or if the platform's algorithm surfaces content selectively. Conversely, users might not change their following behavior but still encounter diverse content through other channels such as trending topics or search. To assess whether the reduction in selective following generates genuine exposure to diverse information, we examine two outcomes: the composition of users' newsfeeds (what content appears) and users' engagement with that content (what they actively interact with).

We estimate specifications parallel to our main following analysis, with dependent variables measuring information consumption over two post-call windows: days [0, 9] and days [10, 30]. The first window captures the immediate information environment shaped by users' pre-existing networks and any follows made in the first days after the call. The second window captures the cumulative effect as users continue to receive content from their modified networks over a longer period. If the changes in following behavior documented in Section 3.3 are meaningful, we should observe increasingly divergent information environments between treated and control users as time progresses.

Our first outcome is net bullish impressions, defined as the total number of bullish messages about firm s that appear in user *i*'s newsfeed during the window, minus the total number of bearish messages. A message appears in user *i*'s newsfeed if it was posted by any user that *i* follows. This measure captures the cumulative sentiment exposure resulting from the user's network structure. It reflects both the composition of the network (who the user follows) and the activity of those followed users (how much they post).

Table 5, columns 1 and 2 report the results. Consistent with the selective following documented by Cookson, Engelberg, and Mullins (2023), we find substantial baseline differences in information environments: bullish users' newsfeeds contain significantly more net-bullish impressions than bearish users' newsfeeds, even over short time horizons. This confirms that selective following generates meaningful differences in the information users observe.

The interaction coefficients indicate that streaming reduces this information gap, though the pattern differs across time windows. In the immediate window (days 0-9), the reduction is modest and not statistically significant, suggesting that users' pre-existing networks continue to shape their newsfeeds in the days immediately following the call. However, in the longer window (days 10-30), the effect strengthens considerably and becomes highly significant. The interaction coefficient indicates approximately a 60 percent reduction in the information gap between bulls and bears. This strengthening over time suggests that the initial changes in following behavior documented in Section 3.3 compound as users continue to receive diversified newsfeeds from their modified networks.

While the impressions measure captures passive exposure to content, it does not tell us whether users actually pay attention to the diverse information in their newsfeeds. Users might see both bullish and bearish messages but selectively engage with only the messages that confirm their priors. To assess active engagement, we examine a second outcome: net liked messages from declared bulls, defined as the number of messages by self-declared bulls that user *i* likes during the window, minus the number of messages by self-declared bears that user *i* likes. On StockTwits, liking a message requires the user to click on it, indicating that they read the content and chose to signal approval or agreement. This measure, therefore, captures deliberate engagement rather than passive exposure.

Table 5, columns 3 and 4 report the results. The baseline differences in selective engagement are even larger than the differences in passive exposure: bullish users like substantially more net-bullish messages than bearish users. This pattern reveals that users engage selectively with the information in their newsfeeds. Even when users' newsfeeds contain some diverse information, they disproportionately like messages that confirm their views. This selective engagement amplifies the echo chamber effect beyond what the network structure alone would generate.

The interaction coefficients show that streaming significantly reduces this selective engagement in both time windows. Unlike the impressions results, the effect on likes is immediate and statistically significant in the short window (days 0-9), suggesting that streaming affects not only the information users observe but also how they interact with that information almost immediately. Bullish users at streamed firms engage more with diverse information, liking fewer bullish messages or more bearish messages than their counterparts at non-streamed firms. The effect strengthens further in the longer window (days 10-30), indicating persistent changes in engagement behavior rather than momentary reactions.

The persistence of effects across both measures is notable. Users exposed to streamed calls continue to observe more diverse information and engage more with that diverse information for at least 30 days after the call. This persistence suggests that the treatment has lasting impacts on users' information environments, not merely transient changes during or immediately after the live event. The modified network structures that users create in the days following a streamed call continue to shape their information consumption for weeks afterward.

The results demonstrate that the reduction in selective following documented in Section 3.3 generates meaningful changes in users' actual information consumption and engagement. Bullish users exposed to streamed calls not only follow fewer bullish users but also see fewer bullish messages in their newsfeeds and engage less frequently with bullish content. The information environment changes are substantial, persistent, and operate through both passive exposure (what appears in newsfeeds) and active engagement (what users choose to interact with).

Having established that streaming changes both network structure and information consumption, we now examine whether these behavioral changes translate into belief revision.

3.5 Echo Chambers, Content Production, and Belief Revision

The results in Sections 3.3 and 3.4 demonstrate that streaming disrupts echo chamber formation: users follow fewer like-minded individuals and consequently consume less confirming content in their newsfeeds. A natural question is whether these behavioral changes translate into actual belief revision or whether users simply adjust their networks while maintaining their original views. To address this, we examine whether users' expressed beliefs change after exposure to streamed calls by analyzing their post-call messaging behavior.

If streaming merely changes information exposure without affecting beliefs, we should observe no change in the content users produce. Conversely, if users genuinely update their beliefs, we should observe them expressing less extreme views in their subsequent posts. We focus on three outcomes: the total volume of posts (to assess whether streaming affects overall engagement), the net sentiment of posts (to measure belief intensity), and the direction of sentiment (to capture whether users maintain or reverse their initial stance).

We estimate specifications parallel to our main analysis, with dependent variables measuring message production over two windows: days [0, 9] following the call and days [10, 30]. The first window captures immediate reactions, while the second captures more gradual belief revision. If belief updating is a deliberate process of incorporating new information into priors, we would expect stronger effects in the later window as users have time to reflect on what they learned during the call.

Table 6 reports the results. Columns 1 and 2 examine total posting volume, measured as the number of messages user *i* posts about firm *s* during each window. The coefficient on *Declared*

Bull is positive, indicating that bullish users post more frequently about the firm following the announcement. However, the interaction coefficient is not significant in either window. This suggests that streaming does not affect how much users post, only the sentiment they express. The absence of a volume effect also helps rule out the concern that our results reflect differential attention or engagement rather than genuine belief revision.

Columns 3 and 4 examine net bullish posts, defined as the number of bullish messages minus bearish messages posted by user *i* about firm *s* during each window. We observe strong baseline persistence: users classified as bullish based on their pre-announcement messages continue to produce substantially more net-bullish messages in the days following the announcement. This baseline persistence validates our classification approach and is consistent with the sentiment persistence patterns documented in prior work.

The interaction coefficients indicate that bullish users exposed to streamed calls produce significantly fewer net-bullish posts in both time windows. In the immediate window (days 0-9), the reduction is modest but statistically significant, suggesting that some users begin moderating their views quickly after exposure to the call and diverse chat discussion. In the longer window (days 10-30), the effect strengthens substantially. The strengthening of the effect over time is consistent with gradual belief revision. Users appear to incorporate the information they encountered during the call progressively rather than making immediate, complete adjustments to their stated views.

Columns 5 and 6 examine a binary measure of belief persistence: an indicator equal to one if user *i* posts more bullish than bearish messages about firm s during the window. This outcome is less sensitive to extreme values (users who post very prolifically) and focuses on the direction rather than intensity of expressed sentiment. The baseline effect confirms that the vast majority of users classified as bullish continue to post net-bullish messages in the aftermath of the call.

The interaction coefficients show that streaming significantly reduces this probability in both windows. In the immediate window (days 0-9), the reduction is modest, indicating that most users maintain their initial sentiment direction immediately after the call. In the longer window (days 10-30), the effect strengthens considerably. While the majority of users maintain their initial sentiment direction, streaming induces a meaningful fraction of bullish users to either moderate their views sufficiently that they post more bearish than bullish messages or to stop posting about the firm entirely.

The temporal pattern across these results provides insight into the mechanism. The fact that effects are present but modest in the immediate window and strengthen considerably over the longer window is inconsistent with social pressure or conformity during the live event, which should generate immediate but potentially transient changes. Instead, the pattern suggests that users gradually incorporate the information they encountered during the call into their beliefs. This interpretation is consistent with Bayesian updating, where agents adjust their priors based on new signals but do not immediately abandon their initial views.

Taken together, the results in this section provide evidence that the disruption of echo chambers documented in Section 3.3 translates into meaningful belief revision. Users exposed to streamed calls do not merely change which users they follow or what content appears in their newsfeeds. They revise the beliefs they express publicly, and these revisions strengthen over time as users integrate the new information they encountered.

3.6 Echo Chambers and Trading Behavior

The results in Section 3.5 show that streaming induces belief revision, as reflected in changes in the sentiment users express in their subsequent posts. We next ask whether these belief changes translate into investment actions. StockTwits allows users to embed trade declarations in messages by explicitly stating actions such as "bought," "sold," "added to position," or "closed position." While these declarations reflect stated (rather than verified) trades, prior work shows that such declarations on financial social media correlate with real trading activity and convey information about users' conviction (Giannini, Irvine, and Shu, 2019; Cookson, Engelberg, and Mullins, 2020; Booker, Curtis, and Richardson, 2023).

To test whether streaming affects trading behavior, we examine whether users who are classified as bullish prior to the earnings announcement are less likely to declare purchases after the announcement when the call is streamed. Our dependent variable is an indicator equal to one if user *i* makes net buy declarations about firm s during the post-announcement window, defined as the number of buy declarations minus the number of sell declarations. We estimate specifications parallel to our main analysis and measure the outcome over two post-announcement windows: days [0, 9] and days [10, 30].

Table 7 reports the results. The coefficients on *Declared Bull* are positive and highly significant in both windows, indicating that users identified as bullish based on their pre-announcement messages are substantially more likely to declare net purchases following the earnings announcement than declared bears. This pattern supports the interpretation that our sentiment-based classification captures meaningful differences in investment positioning and conviction rather than merely differences in communication style.

The interaction term, *Declared Bull* × *Streamed*, is significantly negative in both windows, indicating that streaming reduces bullish users' propensity to declare purchases. The effect is immediate and statistically strong in the short window (days [0, 9]), consistent with streamed calls affecting users' decisions quickly after the announcement. The effect also persists into the longer window (days [10, 30]), although the statistical significance is weaker, suggesting that the trading-response attenuation remains present but is estimated less precisely over longer horizons.

The magnitude is economically meaningful. Relative to the baseline tendency for bullish users to declare net purchases after non-streamed calls, streaming reduces declared buying activity by roughly one-quarter in the immediate window. This attenuation is consistent with the idea that the streamed call, together with the accompanying real-time discussion, exposes bullish users to disconfirming or clarifying information that leads them to temper conviction and reduce confirmatory trading signals in their subsequent posts.

4. Mechanisms

The results in Section 3 demonstrate that streaming reduces echo chamber formation and facilitates belief revision. We now examine the mechanisms underlying these effects by investigating heterogeneity along two dimensions: the characteristics of the earnings calls themselves and the characteristics of the accompanying chat discussions. Understanding the mechanisms is important for both interpreting the findings and assessing the policy implications of streamed calls.

Our analysis tests two related hypotheses about how the streaming feature operates. First, if access to complete, unfiltered disclosure is important, then the quality and content of the earnings call itself should moderate the treatment effect. Calls that are more interactive, more informative, or that surface disconfirming information should generate stronger effects. Second, if the social context in which users process disclosure matters, then the characteristics of the accompanying chat discussion should moderate the treatment effect. Chats that are more active, more diverse in composition, or more substantive in content should generate stronger effects.

To test these hypotheses, we estimate triple-interaction specifications that extend our main analysis in Section 3.3. The basic structure is:

$$\begin{aligned} Follow\ Bull_{i,s,[t+1,t+10]} &= \beta_1 DeclareBull_{i,s,t} + \beta_2 DeclareBull_{i,s,t} \times Streamed_{s,t} \\ &+ \beta_3 DeclareBull_{i,s,t} \times Streamed_{s,t} \times Characteristic_{s,t} + \lambda_i + \alpha_s \\ &+ \gamma_t + \varepsilon_{i,s,t} \end{aligned} \tag{4}$$

where $Characteristic_{s,t}$ is an indicator for a particular call or chat feature (e.g., high interactivity, high chat activity). The coefficient β_2 captures the baseline streaming effect for calls without the characteristic, while β_3 measures how much the characteristic amplifies or attenuates the effect. All specifications include user fixed effects and firm-by-date fixed effects, ensuring that identification comes from within-firm-quarter comparisons of bullish versus bearish users. Standard errors are clustered at the user level.

4.1 Call Characteristics

We begin by examining whether the content and structure of the earnings call itself moderates the treatment effect. If our results are driven purely by the social interaction in the chat, then characteristics of the call should not matter. Conversely, if access to the primary disclosure is important, then calls that are more informative or that surface disconfirming information should generate stronger effects.

We focus on four dimensions of call quality. First, we measure call activity as the number of question-and-answer exchanges between analysts and management during the call. Prior work documents that the Q&A portion of earnings calls contains more valuable information than the prepared remarks, as analysts probe management assumptions and elicit responses to challenging questions (Hollander, Pronk, and Roelofsen, 2010; Lee, 2016; Gow, Larcker, and Zakolyukina, 2021). We classify calls as high activity if the number of Q&A exchanges exceeds the sample median.

Second, we measure analyst sentiment using FinBERT sentiment analysis applied to analyst questions during the call. Analyst questions that express skepticism or raise concerns may be particularly effective at breaking echo chambers because they come from credible, informed sources. We classify calls as low analyst sentiment if the average sentiment score of analyst questions falls below the sample median.

Third, we measure management sentiment similarly by applying FinBERT to management responses during the Q&A. Management's tone may signal private information about firm prospects, and cautious or negative management responses may be especially credible signals that even optimistic investors must acknowledge (Huang, Teoh, and Zhang, 2014). We classify calls as low management sentiment if the average sentiment score of management responses falls below the median.

Fourth, we measure linguistic obfuscation in management responses. Following Bushee, Gow, and Taylor (2018), we decompose the Fog index of management language into an informational component (complexity reflecting genuine information content) and an obfuscation component (complexity reflecting intentional obscurity). We classify calls as low obfuscation if the obfuscation component falls below the median. Clearer language should make information more accessible to retail investors, facilitating belief updating.

Table 8 reports the results. Across all four dimensions, we find that call characteristics significantly moderate the treatment effect. Column 1 examines discussion activity. The triple interaction indicates that the echo chamber reduction effect is substantially stronger when calls feature more Q&A exchanges. The evidence suggests that active exchanges between analysts and management are more effective at disrupting echo chambers than scripted remarks, consistent with discussion promoting deliberation and making it harder for users to sustain divergent views. Column 2 examines analyst sentiment. We find that calls where analysts ask more negative questions generate significantly stronger effects, suggesting critical analyst questions help break echo chambers by surfacing concerns that bullish users might otherwise dismiss.

Column 3 examines management sentiment. The evidence indicates that calls where management expresses more cautious or negative tones also generate significantly stronger effects, consistent with management tone serving as a credible signal that bullish users struggle to dismiss. Column 4 examines linguistic obfuscation. We find that calls with clearer management language generate significantly stronger effects, suggesting that vague disclosures are easier to ignore or interpret in a way that fits existing narratives.

Across all four dimensions, the common theme is that calls that provide clearer, more direct information, particularly when the information is negative, generate stronger disruption of echo chambers. The patterns are inconsistent with a mechanism based purely on social interaction in the chat, and support the view that access to high-quality primary disclosure is a critical component of the treatment. Together, the heterogeneity analysis reveals that echo chambers in financial social media are particularly fragile to information that simultaneously (i) conflicts with prior narratives, (ii) sharply constrains interpretive wiggle room through clear and specific language, and (iii) is publicly vetted through real-time deliberation between management and informed analysts.

4.2 Chat Characteristics

We next examine whether attributes of the earnings call chat predict the strength of echo chamber disruption. We begin by distinguishing between streamed calls with no chat (zero messages) and those with high chat activity (messages by at least 60 unique users, the sample median). For the subset of calls with active chats, we consider a number of specific chat attributes. First, we consider the proportion of declared bearish users participating in the discussion, conjecturing that the effects should strengthen when the chat provides skeptical commentary. Next, we measure whether bullish users are drawn into direct exchanges. Chats with more user-directed messages (via "@username") reflect greater back-and-forth, conversational engagement, where disagreement and rebuttal can surface in real time.[7] We also consider measures of chat content quality: message sentiment (average FinBERT-classified sentiment), length (average words per message), specificity (ratio of named entities to total words), and topic variance (variance of topic assignments across messages). These measures test whether substantive discussion matters or whether any chat activity generates equivalent effects.

Table 9 reports the results. Column 1 examines calls with no chat activity. The triple interaction coefficient is negative but statistically insignificant. In contrast, the triple interaction term in Column 2, which captures calls with high chat activity, is both negative and highly significant. This indicates that calls with substantial discussion lead to significantly stronger reductions in echo chamber behavior, supporting the view that an interactive social context is an important mechanism. In Column 3, we find evidence that calls with a higher proportion of declared bears lead to significantly stronger reductions in echo chamber behavior, suggesting that bullish users are more likely to update their beliefs when they encounter bearish arguments during the call.

[7] We count only directed messages that do not contain profanity to ensure these interactions reflect genuine conversational exchanges rather than insults. Profanity is identified using the Python package "*u/profanitycounter*", which is widely used to flag and filter abusive language on platforms such as Reddit.

Column 4 shows that chats with more directed discussion are associated with significantly stronger reductions in echo chamber formation, consistent with the idea that interactive exchanges make disengagement or selective avoidance more difficult. Columns 5 through 8 examine the measures of content quality. We find that calls with lower sentiment, longer messages, more specific references, and broader thematic coverage produce significantly stronger effects. In each case, the finding is consistent with call chats facilitating genuine belief updating through substantive discussions. Together, the call heterogeneity results suggest that echo chambers weaken most when an authoritative primary source, the earnings call, is paired with diverse, real-time peer discussion.

5. Conclusion

Information echo chambers present a fundamental challenge for market efficiency and investor welfare. When investors selectively consume information that confirms their existing beliefs, the arrival of public information can increase rather than reduce disagreement, leading to persistent mispricing and poor investment outcomes. Building on evidence that earnings releases can amplify financial echo chambers, this paper investigates whether features of the information venue can instead weaken these echo chambers by examining the introduction of livestreamed earnings calls on StockTwits, which embed primary corporate disclosures within an interactive social media environment.

We find that streaming substantially reduces echo chamber formation. Bullish users exposed to streamed calls are less likely to selectively follow other bullish users, consume significantly less confirming content in their newsfeeds, subsequently revise their expressed beliefs, and signal fewer confirming trades in the 30 days following the call. Heterogeneity analyses indicate that both the quality of the earnings call and the characteristics of the accompanying chat discussion are important to these effects. Interactive calls that surface disconfirming information in clear language generate stronger effects, as do chats with active participation, higher proportions of bearish users, and more substantive content.

The analysis provides compelling evidence that social media platform design choices can reduce echo chamber behavior in financial markets. In particular, the results show that integrating primary disclosures with interactive features can partially disrupt the patterns documented by Cookson, Engelberg, and Mullins (2023). Our work extends the corporate disclosure literature by showing that the context in which disclosure occurs matters for its effectiveness, with implications for regulatory debates about disclosure accessibility. We also contribute to broader work on belief polarization and motivated reasoning by highlighting why public information sometimes increases rather than decreases disagreement: when investors consume earnings news through fragmented, asynchronous channels, they can more easily fit information into their existing narratives. Synchronous, shared processing of primary disclosures alongside diverse peer reactions narrows this scope for motivated reasoning.

Several limitations warrant mention. Our sample covers a single platform during a specific time period, and the firms selected for streaming may differ meaningfully from those not selected despite our controls. The effects we document are substantial but do not eliminate echo chambers entirely, and we cannot measure whether the belief revisions we observe improve investment performance or market efficiency. External validity is also uncertain: the earnings call setting features an authoritative primary source, temporal focus, and financial stakes that may not generalize to other contexts where echo chambers form.

Despite these limitations, our findings suggest that shared information-processing environments, where diverse users consume primary disclosures together and observe each other's reactions, can meaningfully shape belief formation and information aggregation. As information consumption increasingly occurs through social media platforms, understanding how information design choices shape these processes becomes important for investors and regulators seeking to improve the quality of collective information processing in financial markets.

References

Acemoglu, D., Ozdaglar, A. and Siderius, J., 2024. A Model of Online Misinformation. *Review of Economic Studies*, 91: 3117-3150.

Allcott, H., Braghieri, L., Eichmeyer, S. and Gentzkow, M., 2020a. The Welfare Effects of Social Media. *American Economic Review*, 110: 629–676.

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M. and Yang, D., 2020b. Polarization and Public Health: Partisan Differences in Social Distancing During the Coronavirus Pandemic. *Journal of Public Economics*, 191: 104254.

Andries, M., and Haddad, V., 2020. Information Aversion. *Journal of Political Economy*, 128: 1990-2034.

Avin, C., Daltrophe, H., and Lotker, Z. 2024. On the Impossibility of Breaking the Echo Chamber Effect in Social Media Using Regulation. *Scientific Reports*, 14: 1107.

Banerjee, S., Davis, J., and Gondhi, N., 2024. Choosing to Disagree: Endogenous Dismissiveness and Overconfidence in Financial Markets. *The Journal of Finance*, 79: 1635-1695.

Bartov, E., Faurel, L., and Mohanram, P., 2018. Can Twitter Help Predict Firm-Level Earnings and Stock Returns? *The Accounting Review*, 93: pp.25-57.

Blankespoor, E., Miller, G.S., and White, H.D., 2014. The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter™. *The Accounting Review*, 89: 79-112.

Bochkay, K., Hales, J., and Chava, S., 2020. Hyperbole or Reality? Investor Response to Extreme Language in Earnings Conference Calls. *The Accounting Review*, 95: 31-60.

Booker, A., Curtis, A., and Richardson, V.J., 2023. Investor Disagreement, Disclosure Processing Costs, and Trading Volume Evidence from Social Media. *The Accounting Review*, 98: 109-137.

Bowen, T., Dmitriev, D., and Galperti, S., 2023. Learning from Shared News: When Abundant Information Leads to Belief Polarization. *The Quarterly Journal of Economics*, 138: 955-1000.

Broockman, D., and Kalla, J., 2025. Consuming Cross-Cutting Media Causes Learning and Moderates Attitudes: A Field Experiment with Fox News Viewers. *The Journal of Politics*, 87: 246-261.

Bushee, B.J., Gow, I.D., and Taylor, D.J., 2018. Linguistic Complexity in Firm Disclosures: Obfuscation or Information? *Journal of Accounting Research*, 56: 85-121.

Campante, F., Durante, R., Hagemeister, F., and Sen, A., 2025. "GenAI Misinformation, Trust, and News Consumption: Evidence from a Field Experiment." NBER Working Paper w34100.

Campbell, J., D'Adduzio, J., and Moon, R., 2023. "Everyone Has an Opinion: The Informativeness of Social Media's Response to Management Guidance." Available at SSRN 3689185.

Chen, H., De, P., Hu, Y., and Hwang, B.H., 2014. Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media. *The Review of Financial Studies*, 27: 1367-1403.

Cohen, L., Lou, D., and Malloy, C.J., 2020. Casting Conference Calls. *Management Science*, 66: 5015-5039.

Cookson, J., Engelberg, J., and Mullins, W., 2020. "Why Don't We Agree? Evidence from a Social Network of Investors." *Journal of Finance*, 75: 173-228.

Cookson, J., Mullins, W., and Niessner, M. 2024. Social Media and Finance. *Oxford Research Encyclopedia of Economics and Finance*.

Cookson, J., Lu, R., Mullins, W., and Niessner, M., 2024. The Social Signal. *Journal of Financial Economics*, 158: 103870.

Cookson, J., and Niessner, M. 2020. Why Don't We Agree? Evidence from a Social Network of Investors. *The Journal of Finance*, 75: 173-228.

Faia, E., Fuster, A., Pezone, V., and Zafar, B., 2024. Biases in Information Selection and Processing: Survey Evidence from the Pandemic. *The Review of Economics and Statistics*, 106: 829-847.

Giannini, R., Irvine, P., and Shu, T., 2019. The Convergence and Divergence of Investors' Opinions Around Earnings News: Evidence from a Social Network. *Journal of Financial Markets*, 42: 94-120.

Golman, R., Hagmann, D., and Loewenstein, G., 2017. Information Avoidance. *Journal of Economic Literature*, 55: 96-135.

Goldman, E., Gupta, N., and Israelsen, R., 2024. Political Polarization in Financial News. *Journal of Financial Economics*, 155: 103816.

Gow, I.D., Larcker, D.F., and Zakolyukina, A.A., 2021. Non-Answers During Conference Calls. *Journal of Accounting Research*, 59: 1349-1384.

Guest, N., Twedt, B., and Vosse, M. M., 2025. Institutional Investors and Echo Chambers: Evidence from Social Media Connections and Political Ideologies. Available at SSRN 4487717.

Hobolt, S., Lawall, K., and Tilley, J., 2024. The Polarizing Effect of Partisan Echo Chambers. *American Political Science Review*, 118: 1464–1479.

Hollander, S., Pronk, M., and Roelofsen, E., 2010. Does Silence Speak? An Empirical Analysis of Disclosure Choices During Conference Calls. *Journal of Accounting Research*, 48: 531-563.

Hirshleifer, D., Peng, L., and Wang, Q., 2025. "News Diffusion in Social Networks and Stock Market." *Review of Financial Studies*, Forthcoming.

Huang, X., Teoh, S.H., and Zhang, Y., 2014. Tone Management. *The Accounting Review*, 89: 1083-1113.

Kuchler, T., and Stroebel, J., 2021. Social Finance. *Annual Review of Financial Economics*, 13: 37-55.

Larcker, D.F., and Zakolyukina, A.A., 2012. Detecting Deceptive Discussions in Conference Calls. *Journal of Accounting Research*, 50: 495-540.

Lee, J., 2016. Can Investors Detect Managers' Lack of Spontaneity? Adherence to Predetermined Scripts During Earnings Conference Calls. *The Accounting Review*, 91: 229-250.

Levy, R., 2021. Social Media, News Consumption, and Polarization: Evidence from a Field Experiment. *American Economic Review*, 111: 831-870.

Matsumoto, D., Pronk, M., and Roelofsen, E., 2011. What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions. *The Accounting Review*, 86: 1383-1414.

Pouget, S., Sauvagnat, J., and Villeneuve, S., 2017. A Mind Is a Terrible Thing to Change: Confirmatory Bias in Financial Markets. *Review of Financial Studies*, 30: 2066-2119.

Rabin, M., and Schrag, J.L., 1999. First Impressions Matter: A Model of Confirmatory Bias. *Quarterly Journal of Economics*, 114: 37-82.

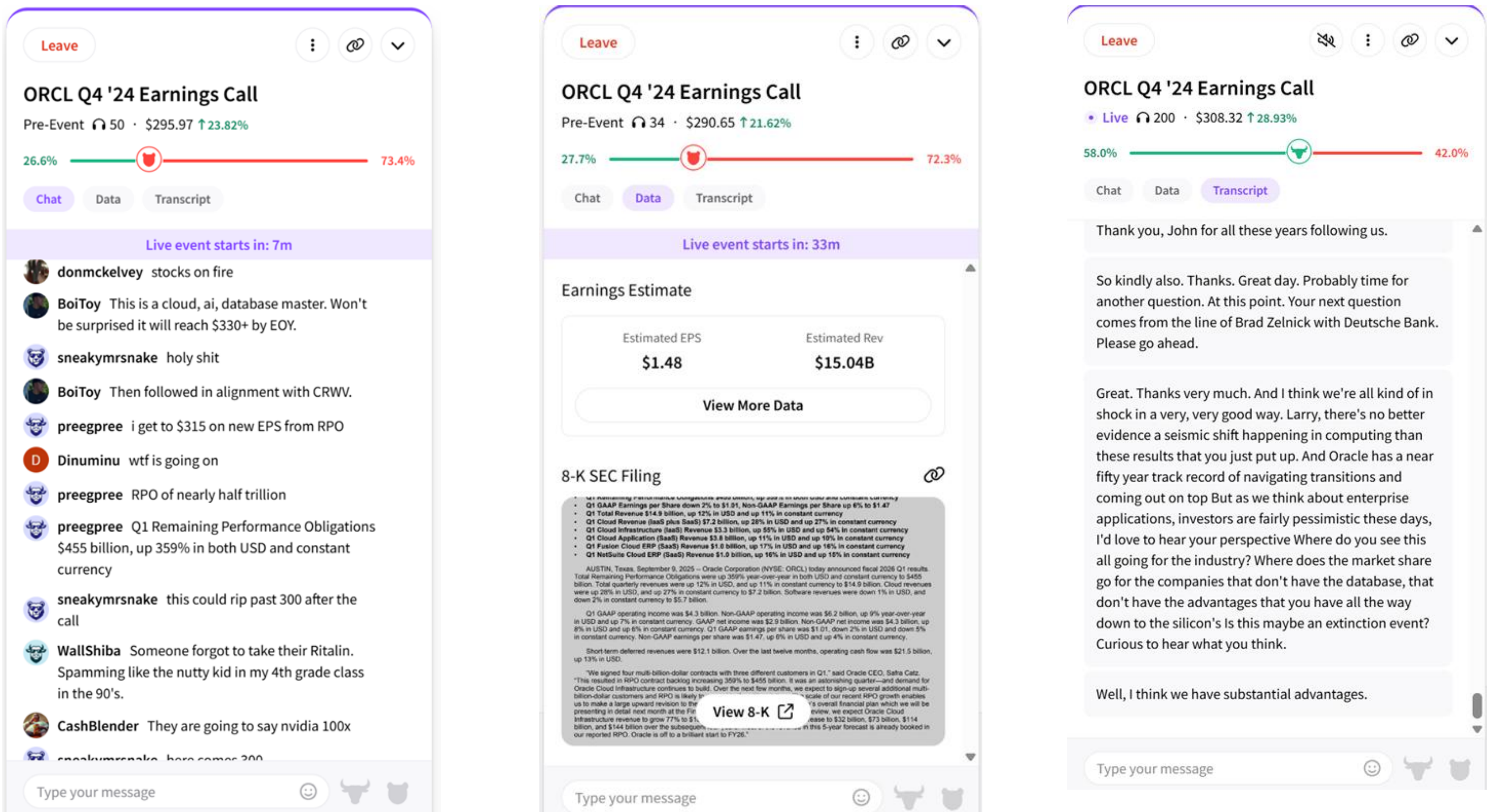
Rennekamp, K.M., Sethuraman, M., and Steenhoven, B.A., 2022. Engagement in Earnings Conference Calls. *Journal of Accounting and Economics*, 74(1), p.101498.

Shearer, E., Eddy, K., Lipka, M., and Matsa, K., 2025. "The Political Gap in Americans' News Sources." Pew Research Center.

Stocking, G., Wang, L., Lipka, M., Matsa, K. E., Widjaya, R., Tomasik, E., and Liedke, J. 2024. "America's News Influencers: The Creators and Consumers in the World of News and Information on Social Media." Pew Research Center.

Appendix A. Example of StockTwits Streamed Earnings Call.

This figure shows the interface for a streamed earnings call on StockTwits, which is divided into three tabs: Chat, Data, and Transcript. The Chat Tab (left panel) displays real-time user commentary before and during the call, along with sentiment indicators and a live countdown. The Data Tab (middle panel) provides earnings estimates, SEC filings, and summary financial data. The Transcript Tab (right panel) shows a live transcript of the call as it unfolds.



Chat Tab **Data Tab** **Transcript Tab**

Appendix B: Variable Appendix

Variable	Calculation / Construction
Age	Natural log of one plus the total year-quarters since the first year-quarter in Compustat. Source: Compustat.
Analyst Following	Natural log of one plus the number of analysts issuing earnings per share forecasts. Source: LSEG.
Declared Bear	Indicator equal to one if at least 50% of a user's messages are declared as bearish during days -10 to -1 before the earnings announcement. Source: StockTwits.
Declared Bull	Indicator equal to one if at least 50% of a user's messages are declared as bullish during days -10 to -1 before the earnings announcement. Source: StockTwits.
Followers	Number of users following the focal user at the end of the prior year-quarter. Source: StockTwits.
Following	Number of users the focal user follows at the end of the prior year-quarter. Source: StockTwits.
High Call Activity	Indicator equal to one if the firm's activity in the earnings call, measured as the total number of distinct interactions, is above the sample median. Source: Capital IQ.
High Chat Activity	Indicator equal to one if the number of unique earnings call livestream chat participants is above the sample median. Source: StockTwits.
High Direct Discussion	Indicator equal to one if the share of directed messages in the chat (messages containing "@<username>," excluding those flagged as profane by the *profanitycounter* Python package) divided by the total number of messages exceeds the sample median. Source: StockTwits.
High Message Length	Indicator equal to one if the average message length, in total number of words, in the earnings call livestream chat is above the sample median. Source: StockTwits.
High Message Sentiment	Indicator equal to one if the average sentiment score of messages in the earnings call livestream chat (classified using FinBERT) is above the sample median. Source: StockTwits.
High Message Specificity	Indicator equal to one if the average message specificity in the earnings call livestream chat is above the sample median. Specificity is the total number of non-numeric entities divided by total words. Source: StockTwits.
High Proportion of Bear Presence	Indicator equal to one if the number of users that are *Declared Bear* present in the earnings call livestream chat is above the sample median. Source: StockTwits.
High Topic Variance	Indicator equal to one if the chat-level standard deviation of LDA topic loadings per message within the earnings call livestream chat exceeds the sample median. Topic loadings are obtained by training a 3-topic LDA model on each chat. Source: StockTwits.
Institutional Ownership	Percentage of shares outstanding held by institutional investors. Source: LSEG.
Leverage	Total debt divided by total assets. Source: Compustat.
Likes Given	Number of likes the user gives to posts about the focal firm during the year-quarter. Source: StockTwits.
Likes Received	Number of likes the user receives on their posts about the focal firm during the year-quarter. Source: StockTwits.

Loss	Indicator equal to one if income before extraordinary items is lower than 0. Source: Compustat.
Low Analyst Sentiment	Indicator equal to one if the average sentiment of analyst questions during the earnings call, classified using FinBERT, is below the sample median. Source: Capital IQ.
Low Management Sentiment	Indicator equal to one if the average sentiment of management presentation and responses to questions during the earnings call, classified using FinBERT, is below the sample median. Source: Capital IQ.
Low Obfuscation	Indicator equal to one if the residual from regressing management's Fog index on analysts' Fog index during the earnings call is below the sample median. This residual isolates the obfuscation component following the approach in Bushee et al. (2018). Source: Capital IQ.
Market-to-Book	Market capitalization divided by book value of equity. Source: Compustat, CRSP.
Net Bull	Indicator equal to one if the total number of *Declared Bull* statuses exceed the total number of *Declared Bear* statuses during days X to Y after the earnings announcement. Source: StockTwits.
Net Bullish Impressions	Indicator equal to one if impressions from bullish users exceed impressions from bearish users during days X to Y after the earnings announcement. A bullish impression is any post shown to a user that originates from a *Declared Bull* on day *t,* and analogously for bearish impressions.
Net Bullish Posts	Indicator equal to one if bullish posts exceed bearish posts during days X to Y after the earnings announcement. A bullish post is post that is declared as bullish on day *t,* and analogously for bearish posts. Source: StockTwits.
Net Buy Declarations	Natural log of one plus buy declarations minus sell declarations during days X to Y after the earnings announcement. A buy declaration is any post on day *t* containing a buy word (roots: *buy-*, *purchas-*, *add-*, *long*, *enter-*); sell declarations analogously use *dump-*, *sell-*, *exit-*, *close*. Source: StockTwits.
Net Follow Declared Bear	Indicator equal to one if bearish follows exceed bullish follows during days 0 to 9 after the earnings announcement. A bullish follow occurs when a user follows another user classified as a *Declared Bull* on day *t,* and analogously for bearish follows.
Net Follow Declared Bull	Indicator equal to one if bullish follows exceed bearish follows during days 0 to 9 after the earnings announcement. A bullish follow occurs when a user follows another user classified as a *Declared Bull* on day *t,* and analogously for bearish follows. Source: StockTwits.
Net Liked Declared Bulls	Indicator equal to one if bullish likes exceed bearish likes during days X to Y after the earnings announcement. A bullish like is any like given to a post shown to a user that originates from a *Declared Bull* on day *t,* and analogously for bearish likes. Source: StockTwits.
No Chat Activity	Indicator equal to one if the earnings call livestream chat has zero chat participants. Source: StockTwits.
Number of Stocks Followed	Number of distinct tickers the user follows at the end of the prior year-quarter. Source: StockTwits.
Pageviews	Natural log of one plus the number of pageviews towards a firm over an hour. Source: StockTwits.

Pageviews	Number of pageviews the user generates toward the focal firm's page during the year-quarter. Source: StockTwits.
Posts	Number of posts made by a user during the fiscal year-quarter. Source: StockTwits.
Price	Average share price over the fiscal year-quarter. Source: CRSP.
Proportion Bearish Posts	Share of a user's posts declared as bearish during the fiscal year-quarter. Source: StockTwits.
Proportion Bullish Posts	Share of a user's posts declared as bullish during the fiscal year-quarter. Source: StockTwits.
Retail Trading	Retail share volume divided by total share volume. Source: CRSP, TAQ.
Return Volatility	Standard deviation of daily returns over the fiscal year-quarter. Source: CRSP.
Return[X,Y]	Buy-and-hold return from trading day X to Y relative to the earnings announcement day. Source: CRSP.
RevenueGrowth	Percentage growth in revenue, relative to the prior year-quarter. Source: Compustat.
ROA	Income before extraordinary items divided by lagged total assets. Source: Compustat.
Size	Natural log of the market capitalization. Source: CRSP.
StockTwits Pageviews	Average daily number of pageviews towards a firm over fiscal year-quarter. Source: StockTwits.
StockTwits Posts	Average daily number of posts referencing the firm over fiscal year-quarter. Source: StockTwits.
StockTwits Sentiment	Average daily net sentiment (bullish minus bearish posts, divided by total posts) over fiscal year-quarter. Source: StockTwits.
Streamed	Indicator equal to one if the earnings conference call is livestreamed on StockTwits. Source: StockTwits.
Surprise	Reported EPS minus the median forecasted EPS, divided by the share price at fiscal quarter end. Source: Compustat, LSEG.
Total Posts	Natural log of one plus the number of posts (in the livestream chat and the firm page) over an hour. Source: StockTwits.
Total Posts	Natural log of one plus the total number of posts during days X to Y after the earnings announcement. Source: StockTwits.
Turnover	Average daily trading volume divided by shares outstanding over the fiscal year-quarter. Source: CRSP.
Unique Posters	Natural log of one plus the number of unique posting users (in the livestream chat and the firm page) over an hour. Source: StockTwits.
Unique Visitors	Natural log of one plus the number of unique users with pageviews towards a firm over an hour. Source: StockTwits.

Cumulative Net Following by Bullish Users

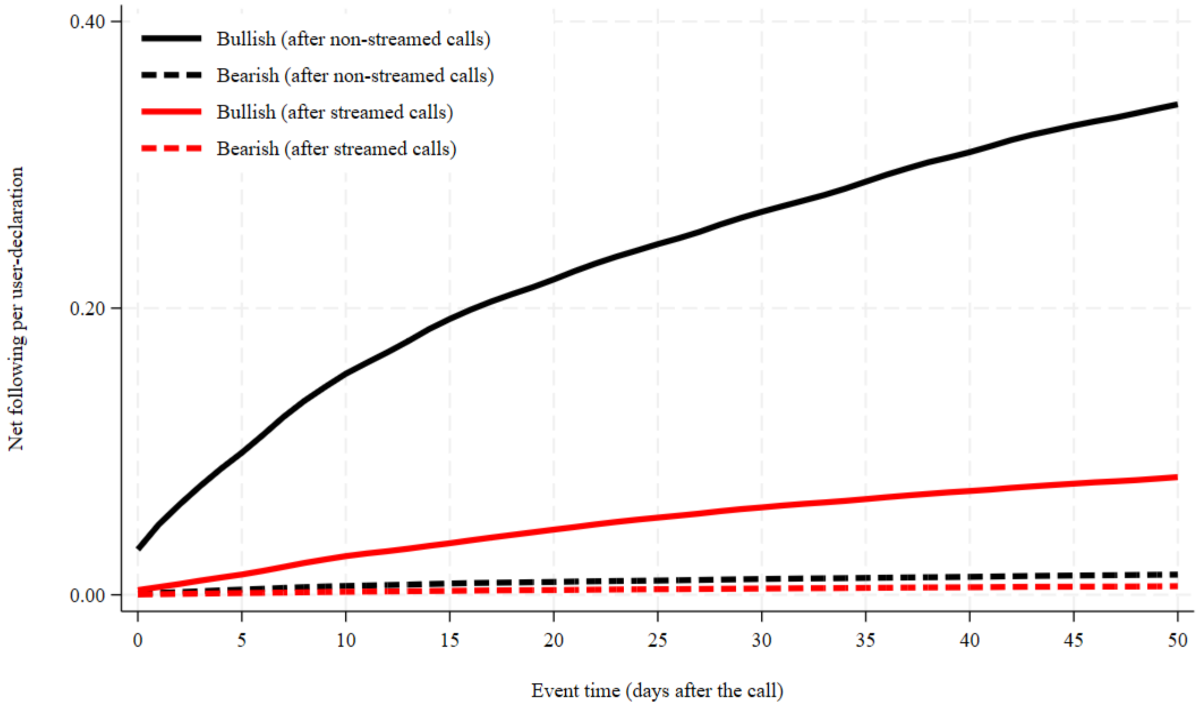


Figure 1. Earnings Call Streaming and StockTwits Following.
The figures plot the cumulative net new following of users who declared bullish sentiment about a firm in the ten days preceding its earnings announcement. Net following is defined as new follows of same-sentiment users minus new follows of opposite-sentiment users, accumulated over the subsequent 50 days. The solid lines show users who declared bullish sentiment, while the dashed lines show users who declared bearish sentiment.

Table 1. Earnings Call and Sample Statistics

Panel A summarizes quarterly coverage of the final sample. *Streamed calls* indicates the number of firm-quarter observations for which the earnings call was livestreamed on StockTwits. *User-declarations* refers to the total number of users classified as *Declared Bull* or *Declared Bear* based on their message activity during days –10 to –1 before the earnings announcement. Panel B reports the distribution of the final sample by user-declaration type, partitioning firm-quarters into those associated with bullish versus bearish user-declarations (as defined over days -10 to -1). Panel C presents the means of the characteristics for all declared users and those users that are declared bulls and declared bears.

Panel A: Sample Overview by Year-Quarter

Year-quarter	Firm-quarters	Streamed calls	User-declarations
2024Q1	1,517	-	18,821
2024Q2	1,661	7	26,582
2024Q3	1,489	556	16,617
2024Q4	1,693	625	21,137
Total	6,360	1,188	84,157

Panel B: Sample Overview by User-Declaration Type

User-declaration type	Firm-quarters	Streamed calls	User-declarations
Bullish	4,552	796	75,115
Bearish	1,808	392	9,042
Total	6,360	1,188	84,157

Panel C: User Statistics for Declared Bulls and Bears

	All declared users	Declared bulls	Declared bears
Posts	43.010	42.479	47.427
Proportion Bullish Posts	0.744	0.828	0.101
Proportion Bearish Posts	0.098	0.017	0.716
Followers	1,071.628	1,125.108	627.384
Following	95.717	96.485	89.342
Likes Given	180.157	196.424	57.157
Likes Received	256.834	278.854	90.322
Pageviews	565.070	600.608	296.345
Number of Stocks Followed	75.657	76.033	72.530

Table 2. Determinants of Conference Call Streaming
This table reports linear probability model estimates of the likelihood that a firm's earnings conference call is livestreamed on StockTwits. The analysis is restricted to 2024Q3 and 2024Q4, the quarters in which livestreaming is available at scale. The dependent variable equals one if the call is streamed in a given quarter. Explanatory variables include firm fundamentals, stock characteristics, ownership and analyst coverage measures, earnings news, retail trading, and StockTwits activity metrics, all defined in Appendix B. Column (1) presents the baseline model, Column (2) adds year-quarter fixed effects, and Column (3) includes firm fixed effects and year-quarter fixed effects. *t*-statistics are reported in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Streamed	
Variable	(1)	(2)	(3)
Age	-0.024	-0.023	0.722
	(-1.51)	(-1.50)	(0.93)
Size	0.015	0.015	-0.073
	(1.43)	(1.42)	(-0.73)
Market-to-Book	0.000	0.000	0.001
	(0.37)	(0.37)	(1.08)
ROA	0.112	0.114	-0.436*
	(0.66)	(0.67)	(-1.91)
Loss	-0.005	-0.004	-0.025
	(-0.19)	(-0.16)	(-0.66)
Leverage	0.002	0.002	-0.005
	(1.28)	(1.27)	(-1.77)
Revenue Growth	-0.009	-0.009	-0.006
	(-0.42)	(-0.43)	(-0.65)
Price	-0.000	-0.000	0.060
	(-0.01)	(-0.01)	(1.65)
Turnover	0.001	0.001	0.001
	(0.57)	(0.56)	(0.67)
Return[-9,0]	-0.066	-0.061	-0.088
	(-0.81)	(-0.76)	(-1.34)
Return[-30,-10]	0.063	0.062	-0.032
	(1.10)	(1.08)	(-0.66)
Return[-90,-31]	0.142***	0.144***	-0.011
	(4.23)	(4.26)	(-0.37)
Return Volatility	-1.568***	-1.565***	-0.248
	(-2.64)	(-2.65)	(-0.70)
Institutional Ownership	0.107	0.106	-0.059
	(1.59)	(1.56)	(-0.42)
Analyst Following	0.054*	0.055*	-0.335**
	(1.86)	(1.86)	(-2.54)
Surprise	-0.005	-0.005	0.004
	(-0.87)	(-0.87)	(0.69)
Retail Trading	-3.330	-3.314	-0.961
	(-0.72)	(-0.71)	(-0.27)
StockTwits Posts	0.008	0.008	0.005
	(0.67)	(0.65)	(0.33)
StockTwits Pageviews	0.004	0.004	-0.012
	(0.40)	(0.42)	(-0.87)
StockTwits Sentiment	-0.065	-0.065	-0.156
	(-1.01)	(-1.01)	(-1.59)

Year-quarter FE	No	Yes	Yes
Firm FE	No	No	Yes
Observations	1,296	1,296	1,296
Adjusted R^2	0.158	0.157	0.710

Table 3. Earnings Call Streaming and StockTwits Platform Engagement.
The table reports estimates of regressions that capture how measures of user engagement on StockTwits vary during the hour of a firm's earnings conference call and whether these effects differ when the call is streamed on the platform. The dependent variables measure firm-level engagement in the hour before the call and the hour of the call: *Pageviews*, *Unique Visitors*, *Total Posts*, and *Unique Posters*. *Conference Call Hour* is an indicator equal to one for the hour in which the earnings call occurs. *Conference Call Hour × Streamed* interacts the conference call hour indicator with an indicator that captures whether the call is livestreamed on the StockTwits platform. All specifications include firm-by-year-quarter fixed effects and date fixed effects. *t*-statistics are reported in parentheses, and *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

Variable	Pageviews (1)	Unique Visitors (2)	Total Posts (3)	Unique Posters (4)
Conference Call Hour × Streamed	0.675***	0.614***	0.701***	0.553***
	(17.85)	(16.81)	(14.15)	(13.49)
Conference Call Hour	0.923***	0.857***	1.059***	0.907***
	(12.60)	(12.50)	(13.29)	(13.79)
Firm × Year-Quarter FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Observations	9,602	9,602	9,602	9,602
Adjusted R^2	0.945	0.932	0.874	0.884

Table 4. Earnings Call Streaming and Echo Chamber Formation

The table reports regressions using user-level observations of net following behavior after earnings announcements. The dependent variable is an indicator for whether a user's net new follows favor bullish accounts over bearish accounts in the post-announcement window from 0 to 9 relative to the earnings announcement date. *Declared Bull* identifies users whose pre-announcement messages are at least 50 percent bullish. *Declared Bull × Call Streamed* is the interaction with an indicator for streamed earnings calls. Specifications include the fixed effects listed in the table. *Net Follow Declared Bulls* is multiplied by 100 for ease of interpretation. *t*-statistics are reported in parentheses, and *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Net Follow Declared Bulls	
Variable	(1)	(2)
Declared Bull × Streamed	-2.348**	-2.888**
	(-2.15)	(-1.94)
Declared Bull	4.839***	4.751***
	(6.47)	(5.78)
User FE	Yes	Yes
Firm FE	Yes	No
Date FE	Yes	No
Firm × Date FE	No	Yes
Observations	84,157	84,157
Adjusted R^2	0.492	0.519

Table 5. Earnings Call Streaming and Post-Announcement Information Consumption

The table reports regressions estimating associations between pre-announcement sentiment classifications and measures of users' subsequent information environment on StockTwits. The dependent variables are *Net Bullish Impressions,* defined as bullish minus bearish message impressions in the user's newsfeed, and *Net Liked Messages* from declared bulls over two post-announcement windows: days [0,9] and days [10,30]. *Declared Bull* identifies users whose pre-announcement messages are at least 50 percent bullish. *Declared Bull × Streamed* is the interaction between this indicator and whether the firm's earnings call was streamed on StockTwits. All specifications include user fixed effects and firm-by-date fixed effects. *Net Bullish Impressions* and *Net Liked Declared Bulls* are multiplied by 100 for ease of interpretation. *t*-statistics are in parentheses, and *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

	Net Bullish Impressions		Net Liked Declared Bulls	
	[0,9]	[10,30]	[0,9]	[10,30]
Variable	(1)	(2)	(3)	(4)
Declared Bull × Streamed	-2.224	-5.454***	-4.099***	-6.224***
	(-1.60)	(-3.75)	(-3.75)	(-5.77)
Declared Bull	9.062***	8.854***	29.170***	22.898***
	(9.22)	(8.85)	(35.60)	(29.73)
User FE	Yes	Yes	Yes	Yes
Firm × Date FE	Yes	Yes	Yes	Yes
Observations	177,333	169,031	281,969	279,567
Adjusted R^2	0.569	0.561	0.529	0.549

Table 6. Earnings Call Streaming and Post-Announcement Posting Behavior

The table reports regressions estimating the association between pre-announcement sentiment classifications and post-announcement message production on StockTwits. Dependent variables include *Total Posts*, *Net Bullish Posts* (bullish minus bearish posts), and an indicator for whether net posts are *Net Bullish*, each measured over two post-announcement windows: days [0, 9] and days [10, 30]. *Declared Bull* identifies users whose pre-announcement messages are at least 50 percent bullish. *Declared Bull × Streamed* is the interaction with an indicator for whether the firm's earnings call was streamed on StockTwits. All specifications include user fixed effects and firm-by-date fixed effects. *Net Bullish Posts* and *Net Bull* are multiplied by 100 for ease of interpretation. *t*-statistics are reported in parentheses, and *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Total Posts		Net Bullish Posts		Net Bull	
	[0, 9]	[10, 30]	[0, 9]	[10, 30]	[0, 9]	[10, 30]
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Declared Bull × Streamed	-0.071	0.053	-3.439***	-7.394***	-2.782**	-6.289***
	(-1.10)	(1.06)	(-3.04)	(-4.95)	(-2.52)	(-4.20)
Declared Bull	0.144***	0.069**	53.091***	45.175***	49.911***	44.472***
	(5.81)	(2.05)	(50.19)	(33.24)	(47.74)	(33.01)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211,973	211,973	211,973	211,973	211,973	211,973
Adjusted R^2	0.563	0.592	0.674	0.699	0.659	0.689

Table 7. Earnings Call Streaming and Trade Decisions

The table reports regressions examining the association between pre-announcement sentiment classifications and users' subsequent trade declarations on StockTwits. *Net Buy Declarations* captures whether a user's buy declarations exceed sell declarations (buy-sell measure) over the post-announcement windows. *Declared Bull* identifies users whose pre-announcement messages in the 10 days before the earnings announcement are at least 50 percent bullish. *Declared Bull* × *Streamed* interacts this indicator with whether the firm's earnings call was streamed on StockTwits. All specifications include user fixed effects and firm-by-date fixed effects. *t*-statistics appear in parentheses, and *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Net Buy Declarations	
	[0, 9]	[10, 30]
Variable	(1)	(2)
Declared Bull × Streamed	-0.172***	-0.222*
	(-2.85)	(-1.79)
Declared Bull	0.681***	1.148***
	(13.74)	(12.06)
User FE	Yes	Yes
Firm × Date FE	Yes	Yes
Observations	211,973	211,973
Adjusted R^2	0.146	0.178

Table 8. Earnings Call Streaming and Echo Chamber Formation: Call Attributes

The table reports regressions estimating how call-level characteristics moderate the association between pre-announcement sentiment classifications and users' subsequent following behavior on StockTwits. The dependent variable is an indicator of whether a user's net new follows after the announcement favor bullish accounts over bearish accounts. Interaction terms combine *Declared Bull*, an indicator of whether the earnings call was streamed on StockTwits, and call-level attributes: *High Call Activity*, *Low Analyst Sentiment*, *Low Management Sentiment*, and *Low Obfuscation*, all defined in the variable appendix. Lower-order interaction terms are omitted for brevity but are included as appropriate in each specification. All regressions include user fixed effects and firm-by-date fixed effects. *t*-statistics are reported in parentheses, and *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Net Follow Declared Bulls			
Variable	(1)	(2)	(3)	(4)
Declared Bull × Streamed × High Call Activity	-7.991***			
	(-2.71)			
Declared Bull × Streamed × Low Analyst Sentiment		-6.741**		
		(-2.24)		
Declared Bull × Streamed × Low Management Sentiment			-6.166**	
			(-2.07)	
Declared Bull × Streamed × Low Obfuscation				-4.492*
				(-1.68)
Lower-order interactions	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes
Firm × Date FE	Yes	Yes	Yes	Yes
Observations	51,696	51,696	51,696	51,696
Adjusted R^2	0.561	0.558	0.561	0.557

Table 9. Earnings Call Streaming and Echo Chamber Formation: Chat Attributes

The table reports regressions examining how chat-level attributes moderate the association between pre-announcement sentiment classifications and users' subsequent following behavior on StockTwits. The dependent variable is an indicator of whether a user's net new follows after the announcement favor bullish accounts over bearish accounts. Each specification includes an interaction between *Declared Bull* and a chat attribute. Columns (1) and (2) consider the full set of calls and interact *Streamed* with indicators for *No Chat* activity and *High Chat* activity. The remaining specifications focus on the subset of calls with active chats and include indicators for *High Proportion of Bearish* participants, *High Direct Discussion*, *Low Message Sentiment*, *High Message Length*, *High Message Specificity*, or *High Topic Variance*, all described in the variable appendix. Lower-order interaction terms are omitted for brevity but included as appropriate in each specification. All regressions include user fixed effects and firm-by-date fixed effects. *t*-statistics appear in parentheses, and *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Net Follow Declared Bulls							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Declared Bull × Streamed × No Chat Activity	-0.504							
	(-0.16)							
Declared Bull × Streamed × High Chat Activity		-2.971*						
		(-1.69)						
Declared Bull × High Proportion of Bearish Participants			-5.969***					
			(-2.82)					
Declared Bull × High Direct Discussion				-2.440*				
				(-1.70)				
Declared Bull × Low Message Sentiment					-3.725*			
					(-1.73)			
Declared Bull × High Message Length						-5.765**		
						(-2.46)		
Declared Bull × High Message Specificity							-3.857*	
							(-1.82)	
Declared Bull × High Topic Variance								-5.031**
								(-2.01)
Declared Bull	4.460***	4.12***	4.654**	3.387*	4.212*	4.945***	4.146**	4.370**
	(5.75)	(5.50)	(2.47)	(1.73)	(1.83)	(2.67)	(2.25)	(2.21)
User FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,157	13,213	13,213	13,213	13,213	13,213	13,213	13,213
Adjusted R^2	0.519	0.623	0.652	0.651	0.651	0.652	0.651	0.651

Earnings Calls and Echo Chambers:
Evidence from the Introduction of Livestreaming on StockTwits

Internet Appendix

December 2025

Cumulative Net Following by Bearish Users

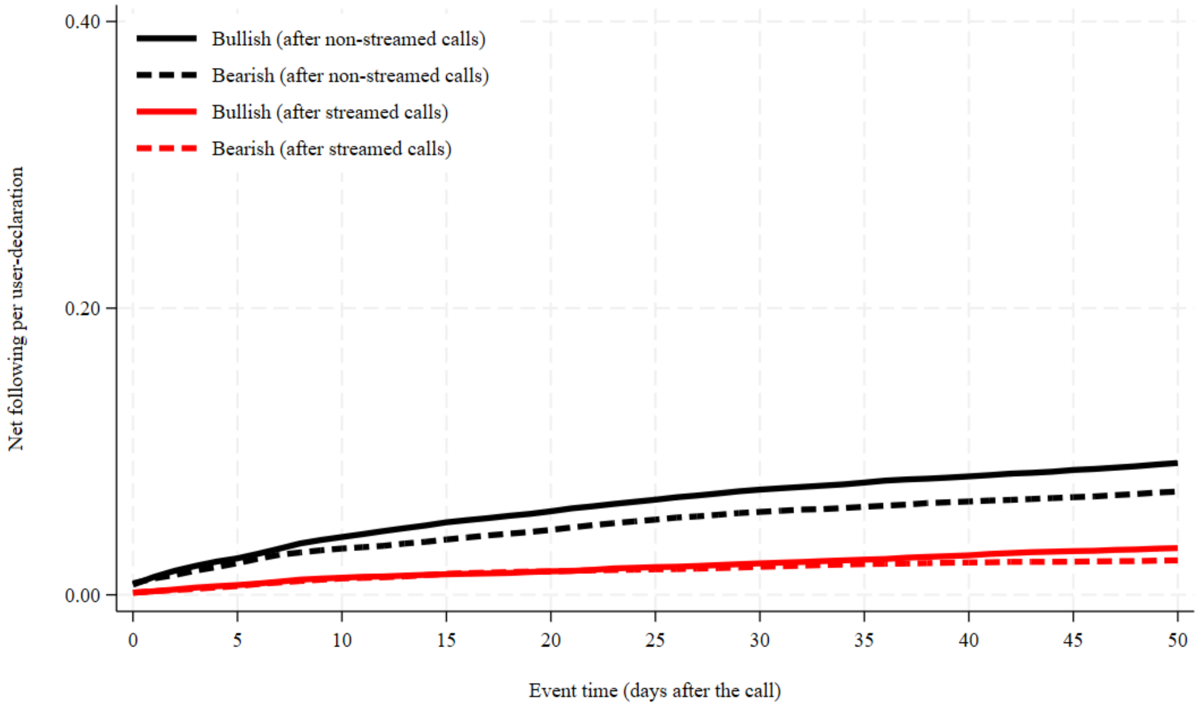


Figure IA1. Earnings Call Streaming and StockTwits following: Bearish Users.
The figures plot the cumulative net new following of users who declared bearish sentiment about a firm in the ten days preceding its earnings announcement. Net following is defined as new follows of same-sentiment users minus new follows of opposite-sentiment users, accumulated over the subsequent 50 days. The solid lines show users who declared bullish sentiment, while the dashed lines show users who declared bearish sentiment.

Table IA1. Sample Construction and Industry Breakdown

Panel A reports the sequential construction of the sample, beginning with all Compustat firm-quarter observations linked to earnings announcement dates in 2024. Observations are removed with each data requirement filter. Panel B summarizes the distribution of the sample across GICS sectors. For each sector, the table reports the number of firm-year-quarters, the number of earnings calls streamed on StockTwits, and the total number of user declarations (messages in which users assign bullish or bearish sentiment to the focal firm).

Panel A: Sample Selection

	Obs. Dropped	Obs. Remaining
Initial sample: All Compustat firm-quarter observations with non-missing earnings announcement dates in 2024		24,867
Less: Observations missing link to StockTwits ticker symbol	-4,277	20,590
Less: Observations missing user-declarations in the window [-10, -1] relative to earnings announcement $t = 0$	-14,230	6,360
Final firm-quarter sample		6,360

Panel B: Sample Overview by GICS-Sector

GICS-Sector	Firm-quarters	Streamed calls	User-declarations
Communication Services	296	56	3,622
Consumer Discretionary	717	204	15,050
Consumer Staples	254	64	1,335
Energy	262	52	846
Financials	563	23	1,192
Health Care	2,120	289	12,167
Industrials	760	176	6,749
Information Technology	978	259	20,820
Materials	240	39	217
Real Estate	125	9	142
Utilities	45	17	45
Total	6,360	1,188	84,157

Table IA2. Sample Descriptive Statistics

The table reports descriptive statistics for the main variables used in the analysis. For each variable, we report the number of observations, mean, standard deviation, and the 25th, 50th, and 75th percentiles. The first panel summarizes firm-quarter characteristics, the second panel summarizes firm-hour measures of call-related traffic and posting activity, the third panel summarizes user-declaration level measures of sentiment, following, posting, and trading behavior in the [0,9] and [10,30] day windows around earnings calls, and the final panel reports firm-call and firm-chat level characteristics capturing call content and chat features. All variables are defined in the Appendix.

Panel A. Firm-Quarter Variables

	Obs.	Mean	S.D.	25th	50th	75th
Streamed	6,360	0.181	0.385	0.000	0.000	0.000
Age	2,931	4.135	0.881	3.401	4.094	4.868
Size	2,931	7.389	2.502	5.701	7.333	9.258
Market-to-Book	2,931	4.693	12.515	1.065	2.670	6.666
ROA	2,931	-0.035	0.107	-0.058	0.000	0.019
Loss	2,931	0.659	0.474	0.000	1.000	1.000
Leverage	2,931	0.672	4.567	0.049	0.426	1.256
Revenue Growth	2,931	0.076	0.566	-0.064	0.018	0.099
Price	2,931	3.112	1.670	1.640	3.072	4.424
Turnover	2,931	0.238	0.576	0.063	0.110	0.192
Return[-9,0]	2,931	0.014	0.140	-0.054	0.004	0.065
Return[-30,-10]	2,931	0.008	0.177	-0.079	-0.008	0.067
Return[-90,-31]	2,931	0.004	0.343	-0.180	-0.028	0.128
Return Volatility	2,931	0.040	0.027	0.021	0.034	0.051
Institutional Ownership	2,931	0.659	0.300	0.443	0.743	0.888
Analyst Following	2,931	2.218	0.792	1.609	2.303	2.890
Surprise	2,931	-0.053	1.181	-0.019	-0.003	0.002
Retail Trading	2,931	0.004	0.014	0.000	0.001	0.002
StockTwits Posts	2,931	5.321	2.451	4.234	5.497	6.900
StockTwits Pageviews	2,931	8.497	3.487	7.484	9.205	10.697
StockTwits Sentiment	2,931	0.224	0.155	0.115	0.216	0.329

Panel B. Firm-hour level variables

	Obs.	Mean	S.D.	25th	50th	75th
Pageviews	9,602	6.352	2.119	4.887	6.261	7.766
Unique Visitors	9,602	5.475	1.939	4.127	5.303	6.661
Total Posts	9,602	2.817	1.846	1.386	2.565	4.007
Unique Posters	9,602	2.490	1.597	1.386	2.303	3.497

Panel C. User-Declaration Level Variables

	Obs.	Mean	S.D.	25th	50th	75th
Declared Bull	84,157	0.893	0.310	1.000	1.000	1.000
Declared Bear	84,157	0.107	0.310	0.000	0.000	0.000
Net Follow Declared Bull	84,157	0.130	0.336	0.000	0.000	0.000
Net Follow Declared Bear	84,157	0.001	0.106	0.000	0.000	0.000
Net Bullish Impressions[0,9]	177,333	0.613	0.487	0.000	1.000	1.000
Net Bullish Impressions[10,30]	177,333	0.646	0.478	0.000	1.000	1.000
Net Liked Declared Bulls[0,9]	281,969	0.573	0.495	0.000	1.000	1.000
Net Liked Declared Bulls[10,30]	281,969	0.506	0.500	0.000	1.000	1.000
Total Posts[0,9]	211,973	2.036	1.063	1.099	1.946	2.773
Total Posts[10,30]	211,973	2.171	1.172	1.099	1.946	2.996
Net Bullish Posts[0,9]	211,973	0.798	0.401	1.000	1.000	1.000
Net Bullish Posts[10,30]	211,973	0.804	0.397	1.000	1.000	1.000
Net Bull[0,9]	211,973	0.767	0.423	1.000	1.000	1.000

Net Bull[10,30]	211,973	0.786	0.410	1.000	1.000	1.000
Net Buy Declarations[0,9]	211,973	0.906	3.011	0.000	0.000	1.000
Net Buy Declarations[10,30]	211,973	1.879	5.834	0.000	0.000	1.000

Panel E. Firm-Call and Firm-Chat Level Variables

	Obs.	Mean	S.D.	25th	50th	75th
Call Activity	51,696	44.323	24.608	29.000	41.000	55.000
Analyst Sentiment	51,696	0.003	0.141	-0.043	0.025	0.072
Management Sentiment	51,696	0.001	0.304	-0.220	-0.022	0.182
Obfuscation	51,696	0.120	1.373	-0.850	-0.053	0.970
Chat Activity	84,157	42.985	218.651	0.000	0.000	0.000
Proportion of Bear Presence	13,213	0.043	0.088	0.000	0.014	0.048
Direct Discussion	13,213	0.006	0.011	0.000	0.002	0.006
Message Sentiment	13,213	-0.009	0.063	-0.032	-0.017	0.019
Message Length	13,213	6.168	1.670	5.415	6.001	6.891
Message Specificity	13,213	0.131	0.156	0.066	0.087	0.121
Topic Variance	13,213	0.036	0.012	0.031	0.034	0.044

Table IA3. Earnings Call Streaming and Echo Chamber Formation: Robustness

The table reports robustness checks for regressions relating pre-announcement sentiment classifications to users' post-announcement following behavior on StockTwits. The dependent variable is an indicator of whether a user's net new follows favor bullish accounts over bearish accounts. Each column applies an alternative sample restriction: users with more than 90 percent bullish messages (Column 1), users active online during the call window (Column 2), only firms with call transcripts in Capital IQ (Column 3), only the 2nd and 3rd quarters of 2024 (Column 4), and users classified as bearish (Column 5). Interaction terms pair *Declared Bull* or *Declared Bear* with an indicator for *Streamed* earnings calls. Specifications include user fixed effects and the firm-level fixed effects listed in the table. Observations and adjusted R^2 values are reported for each column. t-statistics appear in parentheses, and *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively.

	Net Follow Declared Bulls				Net Follow Declared Bears
Variable	> 90% of Messages Bullish (1)	Online Users (2)	Firms with Call Transcripts (3)	2024Q2 - 2024Q3 (4)	Bearish Users (5)
Declared Bull × Streamed	-2.484*	-2.488*	-3.192*	-2.759*	
	(-1.72)	(-1.60)	(-1.78)	(-1.68)	
Declared Bear × Streamed					1.440
					(1.39)
Declared Bull	4.314***	5.112***	5.005***	4.741***	
	(4.63)	(5.73)	(4.95)	(4.40)	
Declared Bear					0.338
					(0.76)
User FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes
Firm × Date FE	Yes	Yes	Yes	No	No
Observations	84,157	78,433	62,937	39,232	84,157
Adjusted R^2	0.490	0.520	0.543	0.574	0.402