Are Gains Quiet and Losses Loud? Emotional Responses to Financial Booms and Crashes Online

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Abstract

Financial events negatively affect emotional well-being, but large-scale studies examining their impact on online emotional expression using real-time social media data remain limited. To address this gap, we propose analyzing Reddit communities (financial and non-financial) across two case studies: a financial crash and a boom. We investigate how emotional and psycholinguistic responses differ between financial and non-financial communities, and the extent to which the type of financial event affects user behavior during the two case study periods. To examine the effect of these events on expressed language, we analyze daily sentiment, emotion, and LIWC counts using quasi-experimental methods: Difference-in-Differences (DiD) and Causal Impact analyses during a financial boom and a financial crash. Overall, we find coherent, negative shifts in emotional responses during financial crashes, but weaker, mixed responses during booms. By exploring emotional and psycholinguistic expressions during financial events, we identify future implications for understanding online users' mental health and building connected, healthy communities.

1 Introduction

Periods of economic uncertainty affect people's daily lives, influencing their financial decisions, emotional states, and patterns of expression. Prior research has linked financial stressors to elevated depression and psychological distress at the population-level (Kokaliari 2018). At a theoretical level, behavioral finance and psychology offer well-established explanations of these effects. In particular, the *loss aversion theory* postulates that individuals experience losses more intensely than equivalent gains, leading to amplified emotional reactions during market downturns (Kahneman and Tversky 2013). Relatedly, the psychological theory of negativity bias suggests that negative events have a stronger effect on people's psychological well-being (Rozin and Royzman 2001).

Although these theories are widely supported by laboratory experiments, surveys, and economic models, understanding how they manifest on people's well-being in everyday life, particularly in real time and at a large scale, remains challenging. Traditional methods rely heavily on retrospective self-reports or aggregated indicators, which are limited in their ability to capture immediate emotional responses, temporal dynamics, and collective sense making during unfolding financial events (Tourangeau, Rips, and Rasinski 2000). In contrast, social media responses provides a naturalistic lens into how people publicly articulate emotions, seek advice, and navigate uncertainty as events unfold (Saha et al. 2021). Moreover, responses can differ based on participation among different online social media communities (Park, Conway, and Chen 2018). During major financial or policy shocks, online discussions often intensify, offering signals of emotional, cognitive, and psychosocial responses related to money and well-being.

Despite this opportunity, existing social media research has mostly focused on isolated financial crises, descriptive sentiment trends, or domain-specific outcomes (e.g., trading behavior), rather than systematically testing how different financial event types affect well-being and emotional responses (Johnson et al. 2023). There is limited empirical evidence examining whether emotional and psycholinguistic responses to the types of financial events differ (e.g., booms vs. crashes) in magnitude, direction, and persistence (Goodell et al. 2023). To address these gaps, we investigate how financial booms and crashes causally shape emotional and psycholinguistic expression in different online communities. Leveraging large-scale Reddit discussions, we compare and identify responses among finance-focused and non-financial communities to financial events. We adopt a quasi-experimental causal design to examine both immediate and sustained effects of financial shocks on online discourse. Our work is guided by the research questions (RQs) below:

RQ1: How do financial booms and crashes shape emotional and psycholinguistic expressions in online financial communities, compared to non-financial communities?

RQ2: Do financial booms and crashes produce sustained and asymmetric emotional responses in financial communities?

We conduct an observational study on Reddit to analyze how user behavior may differ during a financial crash and a boom. We focus on Reddit to study real-time and long-form expressions in common-interest communities (Proferes et al. 2021). Prior work indicates that exogenous shocks, such as COVID-19, affect language and help-seeking behavior (Saha et al. 2020). We further extend this by (a) fo-

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cusing on how financial booms and crashes influence online behavior and (b) contextualizing broader mental-health patterns on how financial stress manifests in online expressions. For RQ1, we use Difference-in-Differences (DiD) to examine emotions and psycholinguistic expressions in a financial group relative to a non-financial group during financial events. For RQ2, we use causal impact (CI) (Brodersen, Hauser, and Hauser 2017) to explore the sustained and asymmetric effects of financial events on emotional responses. *We find that the financial crash triggers stronger, more directionally aligned negative shifts in emotional expressions than weaker, ambivalent shifts during the boom.* Understanding users' well-being during financial events has important implications for (1) designing interventions to mitigate financial stress-related mental health risks, and (2) facilitating healthy online communities.

Ethical Considerations We collect public and anonymized data via APIs that comply with Reddit's terms of service to protect user privacy and avoid disclosing identifiable details. We do not require human studies or ethics board approval.

2 Related Work

Psychological Theories Behind Loss and Gain. Psychologists study *negativity bias*, which proposes that negative events may influence people's well-being more than positive events (Rozin and Royzman 2001). Similarly, behavioral finance studies human decision-making through *prospect theory*, which describes how people evaluate gains and losses asymmetrically (Altman 2010; Kahneman and Tversky 2013), and *loss aversion theory*, which posits that losses are experienced more intensely than gains (Schmidt and Zank 2005). While loss aversion theory has been studied for impacts on investors' financial decisions (Hwang and Satchell 2010), we aim to examine how these psychological theories influence the emotional and psycholinguistic responses of Reddit users during financial booms and crashes.

Psychological Impact of Financial Events. Surveys have reported that global financial crises are associated with depression, anxiety, and stress (Butterworth, Rodgers, and Windsor 2009; Kokaliari 2018). However, surveys are challenging to capture users' real-time emotions during crises, to scale across geographic regions, and to avoid recall bias (Saha et al. 2020). Researchers have used social media such as Reddit to study the impact of financial losses on well-being, finding negative sentiment expressed in financial subreddits during market crashes and losses (Johnson et al. 2023). Despite these insights, there is limited research that leverages real-time social media conversations to investigate psychological theories of financial behavior, such as loss aversion, during both financial booms and crashes. Addressing this gap could provide a more nuanced understanding of how individuals emotionally respond to financial risks and gains in real time, complementing survey-based approaches.

Causal Inference with Social Media Data. Causal inference models can be used to explore causal relationships between events and users' online behavior. For example, researchers have studied causal relations, such as the effect of positive reinforcement on Reddit post quality and frequency (Lambert, Saha, and Chandrasekharan 2025), the effect of Reddit bans on communities on user posting behavior (Chandrasekharan et al. 2017), and the effect of COVID-19 on college students' online mental health expressions.

3 Data and Methods

3.1 Financial and Non-Financial Groups

We identify active, well-established candidate subreddits with a US-centric user base categorized into **(a) financial** and **(b) non-financial** groups. Financial communities focus on topics like personal finance, investing, and debt (*e.g., r/personalfinance*), while non-financial communities focus on general discussions not centered on finance (*e.g., r/explainlikeimfive*). We initially selected **15 financial** and **18 non-financial** most popular candidate subreddits (Table A2), which form the starting pool for constructing balanced groups.

3.2 Event Definitions

We select two economy-wide financial events: a **boom** on *November 8, 2024* (Mikolajczak 2024), and a **crash** on *April 2, 2025* (The Wall Street Journal Staff 2025). Event dates are anchored to public announcement timings rather than market trading dates to better capture users' exposure to the information. For each event, we define 30-day pre- and post-event windows to capture short- to medium-term impacts on online behavior. To establish pre-event comparability between the financial and non-financial groups, we define a **financially stable period** from *April 6, 2023* to *May 6, 2023*, free of major market shocks. This window is used to balance these groups and is not used to answer RQs.

3.3 Reddit Data Collection & Preprocessing

We collect posts, comments, and metadata (e.g., number of comments, upvotes) using the Arctic Shift tool (ArthurHeitmann 2025) during the financial events. We analyze both posts and comments to distinguish between individual self-disclosure and aggregate community responses. We only analyze de-duplicated, English-language, human-written textual content (data processing detailed in Appendix A.2).

3.4 Creating Balanced & Comparable Groups

To isolate the impact of the financial event from the subreddit activity (Stuart 2010), we follow prior studies (Saha et al. 2018) to balance the financial and non-financial groups using pre-event engagement metrics that measure community activity. These include daily post volume, average comments per post, median upvotes per post, daily users, and proportion of textual posts (described in Appendix A.2).

We use *bidirectional pruning* to iteratively compute standardized mean differences (SMDs) across covariates and remove subreddits that contribute most to the imbalance until all covariates fall below the maximum acceptable SMD threshold of 0.25 (Rubin 2001). The final balanced set filtered to **15 financial** and **11 non-financial** subreddits (listed in Table 1) with a maximum SMD of 0.166 (shown in Figure A1). In our study, we analyze ~320K posts and ~2.8M comments, summarized in Table 2 and described in Table A3. To prevent cross-group contamination, we exclude users who were active in both groups during the financial boom (5,246) and the crash (30,206).

Grouping	Subreddit Communities
Financial	r/personalfinance, r/investing, r/bogleheads, r/stocks, r/tax, r/financialindependence, r/economy, r/economics, r/debtfree, r/financialplanning, r/frugal, r/insurance, r/careerguidance, r/creditcards, r/stockmarket
Non-Financial	r/explainlikeimfive, r/trueoffmychest, r/casualconversation, r/askmen, r/tooafraidtoask, r/changemyview, r/asksocialscience, r/askhistorians, r/askacademia, r/parenting, r/seriousconversation

Table 1: List of subreddit communities in balanced groups

	Financial		*Non-Financial*	
Event	**Period**	**#**	**Period**	**#**
Posts				
Boom	08-Oct-24–08-Dec-24	64,473	08-Oct-24–08-Dec-24	66,269
Crash	02-Mar-25–02-May-25	83,551	02-Mar-25–02-May-25	60,943
Stability	06-Apr-23–06-May-23	24,510	06-Apr-23–06-May-23	20,940
Overall		**172,534**		**148,152**
Comments				
Boom	08-Oct-24–08-Dec-24	397,415	08-Oct-24–08-Dec-24	893,878
Crash	02-Mar-25–02-May-25	726,553	02-Mar-25–02-May-25	831,102
Overall		**1,123,968**		**1,724,980**

Table 2: Post and Comment counts in balanced groups

3.5 Conducting Language Analysis

We label the emotion, sentiment, and psycholinguistic patterns in posts and comments to study user language and well-being. Positive, neutral, or negative *sentiment* was labeled using VADER, a sentiment analysis model (Hutto and Gilbert 2014). *Emotions* were labeled as anger, disgust, fear, joy, neutral, sadness, or surprise using a fine-tuned DistilRoBERTa model (Hartmann 2022). We analyzed *LIWC* linguistic features (Tausczik and Pennebaker 2010). We used *affect* (positive emotion, negative emotion, sadness, anger, and anxiety) to measure emotional well-being, *motives* (reward and risk) to measure the sense of losses and gains, and *psychological processes* (cognitive processing, tentativeness, certainty, and achievement) to measure confidence and motivation. For analysis, we calculate the daily proportion of posts containing an expression per group (financial vs. non-financial), accounting for the day$\times$subreddit-level. This normalizes posting frequency across subreddits within each group, assigning equal weights to each subreddit.

4 RQ1: Emotions and Psycholinguistic Expressions During Financial Events

Difference-in-Differences (DiD) We adopted the difference-in-differences (DiD) framework to analyze the causal effect of the financial event on emotional responses in financial groups relative to non-financial groups, using Equation 1 (detailed in Table A5). Fin_i is a group indicator (financial vs non-financial). If pre-event outcomes are parallel, any post-event shift can be attributed to the financial event (detailed in Appendix A.6). The coefficient β_3 isolates changes in outcomes (Y_{it}) in the financial group relative to the non-financial group due to the financial event.

$$Y_{it} = \alpha + \beta_1 Fin_i + \beta_2 Event_t + \beta_3 (Fin_i \times Event_t) + \beta_4 t + \varepsilon_{it} \tag{1}$$

We run DiD for a (i) 30-day and (ii) 10-day pre- and post-event to capture medium- and short-term effects, respectively. DiD's run separately for posts (individual behavior) and comments (community responses) to avoid correlated errors, since comments are directly related to posts.

4.1 DiD Short-Term Results

During the *financial crash*, the financial group's posts increased by 3.63 percentage points (pp) in surprise ($p < 0.001$) and by 3.39 pp in certain language ($p = 0.029$), relative to the non-financial group. The financial group's fear score increased by 0.67 pp relative to the non-financial group ($p = 0.013$). During the *financial boom*, the financial group's posts decreased 4.25 pp in reward-related ($p = 0.006$) and 2.06 pp in anger-related language ($p = 0.048$), while comments decreased 0.87 pp in anger ($p = 0.022$), increased 1.32 pp in joy ($p = 0.028$) and 1.74 pp in cognitive processing ($p = 0.003$) relative to the non-financial group.

Method	Event	Level	Expression	Direction	β_3	p-value
DiD	Crash	Posts	Surprise (Emotion)	↑	0.0363	<0.001
DiD	Crash	Posts	Certainty (LIWC)	↑	0.0339	0.029
DiD	Crash	Comments	Fear (Emotion)	↑	0.0067	0.013
DiD	Boom	Posts	Reward (LIWC)	↓	-0.0425	0.006
DiD	Boom	Posts	Anger (LIWC)	↓	-0.0206	0.048
DiD	Boom	Comments	Joy (Emotion)	↑	0.0132	0.028
DiD	Boom	Comments	Anger (Emotion)	↓	-0.0087	0.022
DiD	Boom	Comments	Cognitive Processing (LIWC)	↑	0.0174	0.003

Table 3: Short-term ($\pm$10 days) effects of financial events

4.2 DiD Medium-Term Results

During the *financial crash*, the financial group's *posts* decreased by 2.22 pp in positive sentiment ($p = 0.045$), decreased by 2.50 pp in achievement-related language ($p = 0.030$), and increased by 2.34 pp in negative sentiment ($p = 0.016$) relative to the non-financial group. The financial group's *comments* increased by 0.98 pp in anger ($p = 0.019$) and by 0.97 pp in sadness ($p = 0.005$) relative to the non-financial group. During the *financial boom*, the financial group's *comments* increased by 0.64 pp in surprise ($p = 0.038$), 1.09 pp in joy ($p = 0.038$), 1.74 pp in positive sentiment ($p = 0.005$), 1.34 pp in reward-related language ($p = 0.027$), 1.40 pp in achievement-related language ($p = 0.021$), and by 1.42 pp in certain language ($p = 0.020$) relative to the non-financial group.

5 RQ2: Sustained Causal Effects of Financial Event on Online Financial Communities

Causal Impact We examine whether financial crashes and booms produce asymmetric, persistent changes in emotional responses within financial communities, focusing on deviations from expected behavior absent a financial event. Comparing the magnitude and persistence of these effects allows us to assess whether crashes exert a stronger influence than booms, consistent with negativity bias and loss aversion. We

Method	Event	Level	Expression	Dir.	Effect	Significance
DiD	Crash	Posts	Positive Sentiment	↓	-0.0222	$p = 0.045$
DiD	Crash	Posts	Negative Sentiment	↑	0.0234	$p = 0.016$
DiD	Crash	Posts	Achievement (LIWC)	↓	-0.0250	$p = 0.030$
DiD	Crash	Comments	Anger (Emotion)	↑	0.0098	$p = 0.019$
DiD	Crash	Comments	Sadness (Emotion)	↑	0.0097	$p = 0.005$
CI	Crash	Posts	Tentativeness (LIWC)	↓	-2.09%	P.P.=99.6%
CI	Crash	Comments	Positive Sentiment	↓	-2.54%	P.P.=100%
CI	Crash	Comments	Negative Sentiment	↑	$+6.49\%$	P.P.=100%
DiD	Boom	Comments	Surprise (Emotion)	↑	0.0064	$p = 0.038$
DiD	Boom	Comments	Joy (Emotion)	↑	0.0109	$p = 0.038$
DiD	Boom	Comments	Positive Sentiment	↑	0.0174	$p = 0.005$
DiD	Boom	Comments	Reward (LIWC)	↑	0.0134	$p = 0.027$
DiD	Boom	Comments	Achievement (LIWC)	↑	0.0140	$p = 0.021$
DiD	Boom	Comments	Certainty (LIWC)	↑	0.0142	$p = 0.020$
CI	Boom	Posts	Sadness (LIWC)	↓	-10.11%	P.P.=100%
CI	Boom	Posts	Anger (LIWC)	↑	$+18.73\%$	P.P.=100%
CI	Boom	Comments	Negative Sentiment	↑	$+4.67\%$	P.P.=100%
CI	Boom	Comments	Joy (Emotion)	↓	-7.87%	P.P.=100%
CI	Boom	Comments	Affect (LIWC)	↑	$+1.53\%$	P.P.=100%
CI	Boom	Comments	Positive Emotion (LIWC)	↑	$+1.62\%$	P.P.=100%

Table 4: Medium-term ($\pm$ 30 days) effects of financial events. DiD reports β_3; causal impact reports relative effects.

estimate these deviations using a Bayesian Structural Time Series model over a 30-day window. For each sentiment, emotion, and LIWC category, we model daily averaged proportions in financial subreddits, using corresponding non-financial subreddit series as covariates. The model is trained on 30 days of pre-event data to predict a counterfactual post-event trajectory, and the causal effect is defined as the difference between the observed and predicted values. Statistical significance is defined as posterior probability $> 95\%$ and the 95% credible interval excluding zero.

5.1 Causal Impact Results

For the *financial boom*, sadness-related language decreased by 10.11% (P.P.% = 100%), but anger-related language increased by 18.73% (P.P.% = 100%) in posts. For the *financial crash*, tentative language decreased by 2.09% (P.P.% = 99.6%), suggesting increased decisiveness in posts during the crisis. *The comments have prominent sustained effects.* For the *financial crash*, negative sentiment increased by 6.49% (P.P.% = 100%), while positive emotion decreased by 2.54 % (P.P.% = 100%). For the *financial boom*, negative sentiment increased by 4.67 % (P.P.% = 100%), and joy decreased by 7.87% (P.P.% = 100%) in comments. Affective language increased by 1.53% (P.P.% = 100%) and positive emotion language by 1.62% (P.P.% = 100%).

6 Discussion

The *DiD analysis* reveals a clear asymmetry in how financial, relative to non-financial, communities react to losses versus gains (Tables 3 and 4). During the crash, the financial group exhibits a unidirectional, negative affect in expressed language, compared to the non-financial group. These include medium-term increases in negative sentiment, anger, and sadness, alongside decreased positive sentiment and achievement-oriented language. *We interpret these shifts as signals of increased distress and negative emotional responses during periods of financial strain.* These effects appear in both posts and comments, but medium-term effects are more prominent in comments, suggesting that *community-level interactions may sustain and amplify the negative emotional responses*. In contrast, these outcomes are weaker and more heterogeneous during the financial boom. Specifically, comments show moderate increases in positive sentiment, surprise, joy, achievement, certainty, and reward-oriented language. In contrast, post-level effects are short-lived, characterized by a conflicted reduction in reward-oriented language. Hence, *these inconsistent signals do not reflect clear or sustained shifts in mental well-being during the boom.*

The *causal impact analysis* also supports this asymmetric pattern (Table 4). During the crash, community responses show fewer but more coherent negative effects, including increases in negative sentiment and decreases in positive sentiment. Financial boom produces mixed impact: posts exhibit decreased sadness but increased anger, while comments show increased negative sentiment, decreased joy, and increased use of affective and positive language. This incongruity suggests that crashes have a more pronounced negative impact on affect than booms at the community level. Taken together, *our findings suggest that financial crashes serve as stronger and more persistent stressors in online communities than financial booms in fostering positive engagement*. This is consistent with the asymmetric responses predicted through the behavioral theory of loss aversion.

7 Conclusion

To conclude, we analyze emotional and psycholinguistic responses to a financial boom and crash across matched financial (15) and non-financial (11) groups using quasi-experimental methods. Both analyses reveal a common pattern: *crashes trigger stronger, more directionally aligned negative shifts in emotional and psycholinguistic expressions compared to weaker, ambivalent shifts due to booms*. Heterogeneous boom signals suggest that positive financial events do not uniformly translate to collective positivity. *While posts capture short-term individual affect, comments significantly sustain and amplify these responses, especially during the crash.* Our results align with empirical findings of past studies on loss aversion (Schmidt and Zank 2005) and contribute to the use of social media data to explore users' real-time responses to financial events.

Beyond financial decision-making, our findings complement prior research on how high-stakes negative events influence online behavior, such as the impact of the COVID-19 pandemic on college students' mental health expressions (Saha, Kotakonda, and De Choudhury 2025). The pronounced negative shifts in emotional responses during the crash align with prior work on the psychological effects of financial stress (Sturgeon et al. 2016) and motivate similar mental-health studies. By incorporating psycholinguistic patterns in response to financial stressors, our findings can augment prior frameworks of understanding people's mental health, such as identifying suicidal ideation (Shimgekar et al. 2025), depression (De Choudhury et al. 2013), or stress levels (Guntuku et al. 2019) during financial crashes. Building on prior social support research (De Choudhury and De 2014; Yang et al. 2019), these insights can also inform event-aware interventions and platform designs that incorporate resource recommendations (e.g., support links during financial crises) to reduce stress-related mental health risks.

Limitations and Future Directions. Our work has limitations, which also suggest interesting future directions. Our work focuses on US-centric events and Reddit; cultural and platform-specific differences may affect responses across geographies and social-media platforms, which we leave for future work. While we present results from two notable case studies, we recognize that they may not generalize to all financial events. Rather, we provide a framework for studying online emotional responses to financial events, which can be extended to future case studies. Although we follow a quasi-experimental design, we cannot claim "true" causality because counterfactual responses cannot be observed. Additionally, both frameworks depend on stable pre-event relationships between the financial and non-financial groups and may under-capture short-term, volatile effects, especially due to anticipatory market behavior and aggregation choices. In the future, these limitations can be addressed by explicitly modeling such behavior and exploring alternate, higher-resolution counterfactual constructions.

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A Appendix

A.1 Data Details

We summarize the Reddit metadata that we collect in Table A1.

Reddit Variable	Description
id	Post and comment id
subreddit	The name of the subreddit
author	Reddit username of the post author
created_utc	Time of creation of the post
title	The title of the post
selftext	The text content of the post
num_comments	Number of comments on the post
ups	Upvotes received on the post
upvote_ratio	Upvotes/Total Number of Votes
subreddit_subscribers	Number of Subscribers on the Subreddit

Table A1: Summary of the raw data variables that we will use for our analysis.

A.2 Data Preprocessing Details

We detail our data preprocessing steps below.

Content Exclusions We filtered the raw data and excluded posts and comments that are irrelevant to conversational analysis:

- NSFW, spoilers, locked or archived posts by using the flags: `over_18`, `spoiler`, `locked`, and `archived`.
- Poll posts by using the flag, `poll_data`.
- Deleted/removed posts and comments, identified using the markers in the title and text for posts and the body for comments ("[removed]", "[deleted]").
- We also exclude comments shorter than 10 characters to exclude low-information responses such as *lol, thanks, okay*.

Automoderator and bot content We excluded posts and comments created by `Automoderator` and bot accounts, which we identified using conservative bot heuristics (username ends in _bot or -bot, or names that contain `bot` as a unique token).

URL Handling We extracted and counted all URLs from the `selftext` field in posts and the `body` field in comments. The following features were generated, which may be useful in our analysis: `has_url`, `count_url`, `url_domains`. We then replaced the URLs in the text with the token `<URL>`, while preserving the Markdown text. This helped us reduce lexical noise while retaining semantic context.

Removing the duplicates We removed duplicate posts based on the same `id`, or a combination of `title, text, selftext`. This helped us eliminate duplicate posts without losing the revised versions. Additionally, we also remove duplicate comments based on the `id` field.

Time Normalization We converted the data timestamps to Eastern Time (America/New York). It is crucial to align on ET time because major US indices and market events are timestamped in ET. We use ET in our data analysis.

Language filter We used the English-only posts and comments for our analysis. The raw data does not have any language markers. These were generated using the `langdetect` module in Python.

Text Normalization We normalized `author`, `title`, and `selftext` to lowercase and Unicode, and normalized spacing. We created `clean_text` by combining the canonized `title` and `selftext`. We use the same normalization process on the `body` field of the comments to create the `clean_text` field, which is used in the downstream analysis.

Removing Overlapping Users For the financial crash, we excluded 1,186 users for posts and 29,020 users for comments. For the financial boom, we exclude 940 users for posts and 4,306 users for comments.

A.3 Matching Reddit Communities

Engagement Metrics Details To match Reddit communities to create two comparable financial and non-financial groups we collect the following variables: calendar day average posts per day (measures how active a subreddit is daily), average number of comments per post (measures the mean magnitude of discussion of a post), median upvotes per post (captures the typical community approval of a post while being robust to extremely viral posts), average number of unique users per day (reflects the size of the active user base in the community), and has_text (indicates the percentage of posts that have textual content rather than only links or media; this allows our analysis to focus on text-based outcome variables).

Reddit Communities in Unbalanced Financial and Non-Financial Groups We include a list of subreddits included in the financial and non-financial groups before the balancing procedure in Table A2.

Grouping	Count	Subreddit Communities
Financial	15	r/personalfinance, r/investing, r/bogleheads, r/stocks, r/financialindependence, r/economy, r/economics, r/tax, r/debtfree, r/financialplanning, r/frugal, r/insurance, r/careerguidance, r/creditcards, r/stockmarket
Non-Financial	18	r/explainlikeimfive, r/trueoffmychest, r/casualconversation, r/askmen, r/tooafraidtoask, r/changemyview, r/asksocialscience, r/askhistorians, r/askacademia, r/parenting, r/seriousconversation, r/advice, r/askdocs, r/legaladvice, r/nostupidquestions, r/relationship_advice, r/offmychest, r/relationships

Table A2: List of subreddit communities in unbalanced financial and non-financial groups.

A.4 Descriptive Statistics for Reddit Posts

We include a summary of statistics for the Reddit posts we collected across the financial stable, boom, and crash periods in Table A3.

A.5 Descriptive Statistics for Reddit Comments

We include a summary of statistics for the Reddit comments that we collected across the financial boom and crash periods in Table A4.

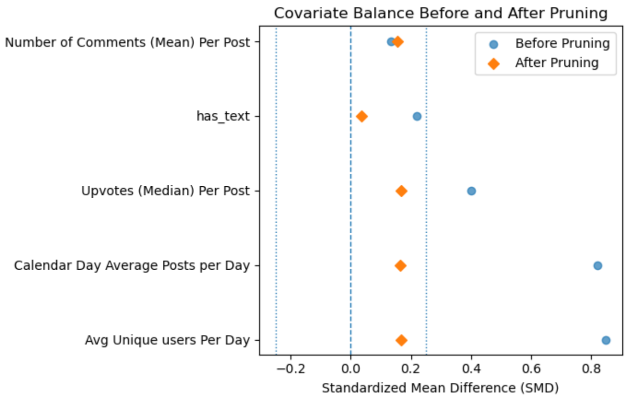

Figure A1: Love plot of Covariate Balance (SMD).

Period	Metric	Financial	Non-Financial
Financially Stable			
	Calendar Day Average Posts per Day	765.938	654.375
	Number of Comments (Mean) Per Post	18.386	30.225
	Upvotes (Median) Per Post	1.000	2.000
	Avg Unique Users Per Day	744.323	648.226
	has_text	0.873	0.740
	Average_sentiment	0.387	0.740
	Total Number of Posts	24,510	20,940
	Total Number of Posts with Text	21,552	15,620
	Number of Subreddits	15	11
Financial Boom			
	Calendar Day Average Posts per Day	1,039.887	1,068.855
	Number of Comments (Mean) Per Post	14.359	30.183
	Upvotes (Median) Per Post	1.000	1.000
	Avg Unique Users Per Day	999.967	1,021.656
	has_text	0.916	0.856
	Average_sentiment	0.398	0.151
	Total Number of Posts	64,473	66,269
	Total Number of Posts with Text	59,125	56,789
	Number of Subreddits	15	11
Financial Crash			
	Calendar Day Average Posts per Day	1,347.597	982.952
	Number of Comments (Mean) Per Post	21.606	30.483
	Upvotes (Median) Per Post	1.000	1.000
	Avg Unique Users Per Day	1,257.590	953.082
	has_text	0.876	0.863
	Average_sentiment	0.326	0.155
	Total Number of Posts	83,551	60,943
	Total Number of Posts with Text	73,215	52,653
	Number of Subreddits	15	11

Table A3: Summary of statistics for collected data during financially stable, boom, and crash periods for the financial and non-financial groups.

Metric	Boom	Crash
Comments (Total)	1,291,293	1,557,655
Financial Group	397,415	726,553
Non-Financial Group	893,878	831,102
Posts with $\geq$1 Comment (%)	79.8	79.2
Posts with 0 Comments (%)	20.2	20.8
Comments per Post: Mean	12.37	13.48
Comments per Post: Median	4.00	4.00
Comments per Post (Financial Group): Mean / Median	7.64 / 3.00	10.68 / 3.00
Comments per Post (Non-Financial Group): Mean / Median	17.07 / 5.00	17.47 / 5.00
Comment Length (words): Mean	58.6	53.8
Comment Length (words): Median	35.0	31.0
VADER Sentiment: Mean	0.189	0.138
VADER Sentiment: Median	0.202	0.064

Table A4: Descriptive statistics for Reddit comments during the financial boom and crash periods. We report statistics for financial and non-financial communities after preprocessing.

A.6 Difference-in-Differences

DiD Equation Definitions We define the variables in our DiD framework in Table A5.

Variable	Variable Definition
Y_{it}	Daily outcome for group i on day t
α	Baseline outcome for the non-financial group prior to the financial event
Fin_i	Indicator equal to 1 for the financial group and 0 for the non-financial group
β_1	Baseline difference between the financial and non-financial groups before the financial event
Event_t	Indicator equal to 1 on and after the financial event (boom/crash) date
β_2	Post-event (boom/crash) change for the non-financial group
$\text{Fin}_i \times \text{Event}_t$	Interaction term, equal to 1 for observations in the financial group on and after the event date, and 0 otherwise
β_3	Coefficient of the interaction term, which captures the additional change in Y_{it} that the financial group experienced after a financial event relative to the non-financial group
t	Linear time trend controlling for smooth temporal dynamics
β_4	Average daily trend in the outcome variable
ε_{it}	Error term; standard errors are HAC-robust

Table A5: Summary of DiD model variables and coefficients

DiD Assumptions The primary assumption for the validity of DiD results is that the trends between the non-financial and financial groups should be parallel in the pre-event period. As an example, we present the graph trends (7-day rolling averages) for positive and negative sentiments for the financial crash for posts in Figure A2 and for comments in Figure A3. We present example sentiment trends for the financial boom for posts in Figure A4 and for comments in Figure A5. We rely on visual inspection and observe a fairly parallel trend between the financial and non-financial groups for both positive and negative sentiments in posts and comments across both events. This provides reasonable support to the DiD assumption.

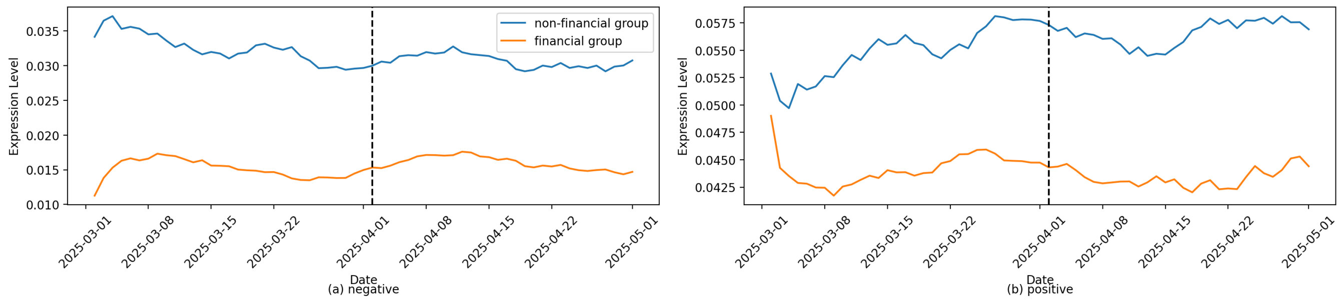

Figure A2: Daily sentiment levels (7-day rolling average) in posts during the financial crash

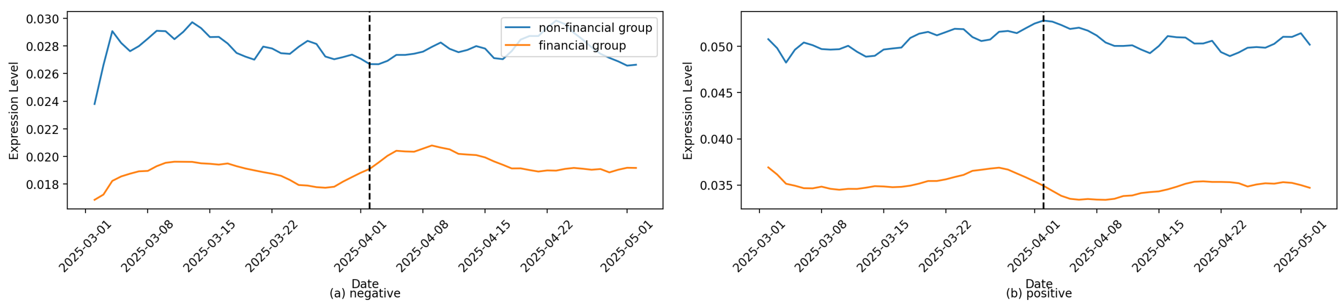

Figure A3: Daily sentiment levels (7-day rolling average) in comments during the financial crash

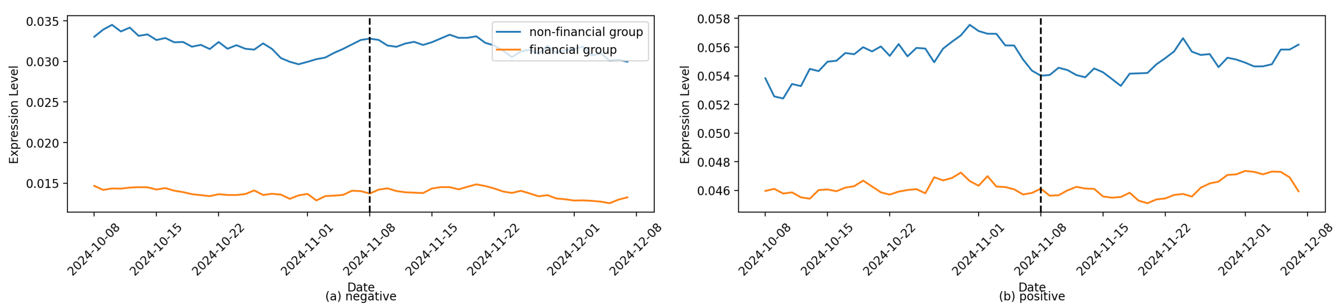

Figure A4: Daily sentiment levels (7-day rolling average) in posts during the financial boom

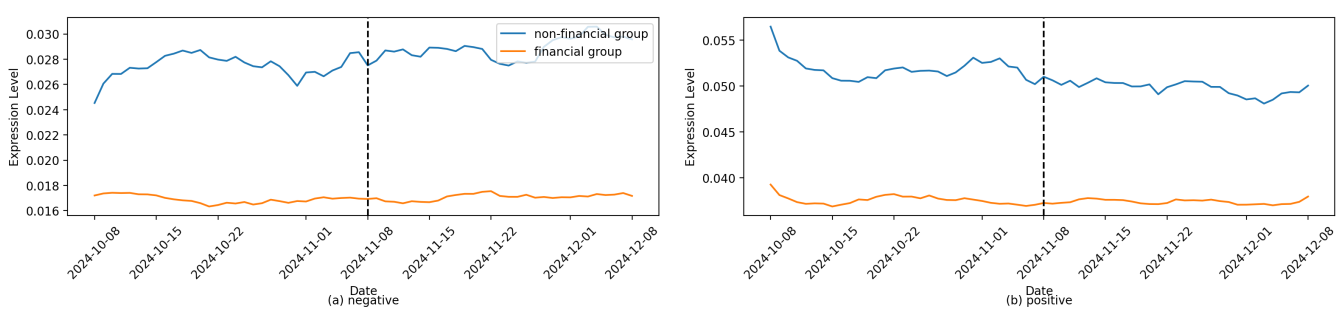

Figure A5: Daily sentiment levels (7-day rolling average) in comments during the financial boom