Ideology-Driven Social Media Opinions and Market Responses to Polarizing Boycotts

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Abstract

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Boycotts triggered by public companies' practices perceived as ideologically polarizing can lead to negative investor reactions. In this study, I examine how the stock market responds to such boycotts and whether ideology-driven social media discourse shapes this response, given investors' increasing reliance on social media information for decision-making. On average, polarizing boycotts are associated with a 1% (2.3%) drop in equity value over the 7 (60) trading days after gaining online traction. Immediate price decline is more pronounced when social media discussions are dominated by users ideologically aligned with the boycotters, particularly when their posts attract online engagement, emphasize financial impact, or come from influential, prolific users. I also find modest evidence that return volatility following boycotts increases when the ideological beliefs of social media posters are more diverse. My findings suggest that polarizing boycotts against corporate actions have stock market ramifications, and that ideology-driven social media opinions seem to amplify both price decline and volatility.

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1. Introduction

In the U.S., many issues such as climate change, gun policy, and LGBTQ rights are highly politicized. In this divisive environment, companies may find themselves, whether intentionally or unintentionally, entangled in polarizing issues, which can provoke public backlash and lead to negative investor responses. For instance, in 2023, Anheuser-Busch and Target faced boycotts from conservatives over their LGBTQ-themed marketing, followed by declining stock prices and analyst downgrades.[1] On the other hand, Home Depot unintentionally became entangled in controversy when a former executive who retired two decades ago donated $1.75 million to controversial Republican Senate candidate Herschel Walker, sparking boycotts by liberals.[2] Nowadays, social media platforms such as X are central hubs where boycott discussions unfold and have become an important source of information for investors.[3] The accessibility of these platforms also allows ideology-driven opinions to proliferate. If investment-focused posts are influenced by ideology, investor reaction to boycotts could be shaped by such discourse, given the close connection between polarizing issues and politics. In this study, I examine how the stock market responds to the polarizing boycott and how ideology-driven social media discourse shapes this response.

I conjecture that ideology can influence how investment-focused social media posters interpret boycott-related news for financial or nonfinancial reasons. From a financial perspective, recent studies suggest that, faced with the same event, individuals with different ideological beliefs may acquire different information or interpret the same information differently, leading to divergent investment opinions (e.g., Cookson et al., 2020; Meeuwis et al., 2022; Kempf et al.,

[1] See: https://www.axios.com/2023/06/16/corporate-america-pride-backlash-stocks.
[2] See: https://www.newsweek.com/home-depot-clears-rumors-donations-herschel-walkers-campaign-1750033.
[3] Note that Twitter was rebranded as "X" in July 2023. In this paper, I use the term "Twitter" to refer to data, tools, and services that preceded the rebranding, such as the Twitter Academic API and the Twitter RoBERTa model.

2023). Therefore, investment-focused social media posters ideologically aligned with boycotters may be more likely to consume news from or adopt the views of like-minded partisan sources. This tendency can be exacerbated by selective exposure to confirmatory information within social media echo chambers (Cookson et al., 2023). As a result, these users may be more likely to express negative opinions towards the boycotted firms. In contrast, those ideologically opposed to boycotters are likely to conclude the opposite. From a nonfinancial perspective, social identity theory argues that shared identity increases the extent to which individuals identify with a group (Tajfel and Turner, 1986) and vice versa. During boycotts, investment-focused social media posters ideologically aligned with boycotters may experience lower identity congruence with the boycotted firm, prompting them to voice more negative opinions online.[4]

Prior academic and practical literature extensively documents that investors acquire and trade on information from social media platforms such as X and StockTwits (e.g., Cookson and Niessner, 2020; Rakowski et al., 2021; CFA Institute, 2024.) For example, a 2023 Brunswick survey of institutional investors found that over 90 percent of respondents said they used social media to investigate investment decisions.[5] Therefore, following ideologically polarizing boycotts, ideology-driven investment opinions on social media could exacerbate market outcomes costly to boycotted firms and their shareholders, such as price declines and excess volatility. Specifically, if users ideologically aligned with boycotters express more negative sentiment about the boycotted firms, I expect the market to react more negatively to polarizing boycotts when a higher share of posts come from such users. In addition, theory suggests that greater disagreement among investors about the value of a stock is associated with more trading

[4] For brevity, I use the terms "investment-focused social media posters" and "social media posters" interchangeably throughout this paper. These terms only refer to users who reference the boycotted firms' cashtags in their posts; users who mention boycott-related hashtags (e.g.,#boycottcocacola) without referencing cashtags are excluded.
[5] See: https://www.brunswickgroup.com/app/uploads/Digital-Investor-Survey-Two-Page-Summary.pdf.

and higher realized volatility (Banerjee and Kremer, 2010). Therefore, I test whether disagreement about boycotts on social media stemming from conflicting ideological beliefs is associated with heightened abnormal turnover and volatility.

However, there are reasons why ideology-driven investment opinions on social media might not affect market responses to polarizing boycotts. To begin, prior research finds mixed evidence on whether ideology-driven boycotts have a meaningful negative impact on firm performance, as boycotts are often counteracted by buycotts, whereby consumers intentionally buy products to support boycotted firms. While Chavis and Leslie (2009) find that the boycott of French wine in response to France's opposition to the Iraq War led to a sustained decline in wine sales, recent studies (Jin et al., 2024; Wang and Lu, 2022; Liaukonyte et al.; 2023) find that buycotts can offset the negative sales effects of boycotts. Thus, it is unclear whether investors will deem boycott news financially relevant and react to it at all. Second, if investment opinions expressed towards boycotted companies on social media are predominantly driven by ideological fervor and lack economic substance, investors may disregard such opinions as noise that is irrelevant to their trading decisions. Therefore, it is an open question whether ideology-driven investment opinions on social media affect how the stock market responds to boycotts.

Studying the impact of ideology-driven social media discourse on market responses to polarizing boycotts involves three empirical challenges: first, identifying polarizing boycotts; second, determining social media posters' sentiment towards boycotted firms; and third, identifying these posters' ideological leanings. To address the first challenge, I use X trending topics to construct a sample of 125 boycotts resulting from corporate actions or statements related to polarizing issues, as identified by the USC polarization index (USC Center for Public Relations, 2022). X trending topics are viral topics prominently displayed on x.com and the mobile app and frequently covered by the news media. This feature raises the likelihood that social media posters are aware of the backlash. For each boycott in my sample, I classify its prevailing ideological belief by reading the posts and referencing contemporaneous news articles, ending up with 80 (64%) boycotts consistent with liberal ideological beliefs and 45 (36%) boycotts consistent with conservative ideological beliefs.[6]

Turning to the second challenge, I analyze the 77,190 posts containing the boycotted firms' cashtags—the dollar sign followed by a ticker symbol—posted when boycotts trended on X. Including a firm's cashtag in posts indicates awareness of and interest in its stock, so posters who do so likely have interest or expertise in investment. This approach is similar to methodologies in Jia et al. (2020) and Campbell et al. (2023), which use posts referencing cashtags to capture the social media discourse pertaining to public companies. To gauge social media sentiment towards boycotted companies, I instruct ChatGPT (GPT-4) to classify post sentiment towards the boycotted firms (i.e., entity-level sentiment) as positive, neutral, or negative. Comparing manual and model classification results within a random sample of 500 posts, GPT-4 achieves a 76% (72%) accuracy (F1) score, outperforming Twitter RoBERTa-base, the Loughran-McDonald dictionary (Loughran and McDonald, 2011), and FinBERT.[7]

To address the third challenge of classifying social media posters' ideological beliefs, I follow an established methodology in political science that detects social media user ideology based on the accounts they follow (e.g., Barberá, 2014; Halbertstam and Knight, 2016). Specifically, I compile a list of 2,072 partisan X accounts and identify which accounts each

[6] See Appendix IA2 for detailed boycotter ideology classification procedures.
[7] Accuracy is the proportion of all classifications that are correct. The F1 score measures an algorithm's precision and recall. A score of 1 indicates perfect precision and recall, and a score of 0 indicates zero precision or recall.

poster follows. I classify a poster as a liberal (conservative) if she follows more liberal (conservative) accounts than conservative (liberal) ones.

To confirm that social media posters' ideological beliefs affect their sentiment towards boycotted firms, I test whether social media posters ideologically aligned with boycotters express more negative opinions towards the boycotted firm, and vice versa. While it is possible for ideological beliefs to shape online investment opinions due to financial value or identity congruence-related reasons, posters may intentionally distance themselves from political motivations to be seen as credible financial commentators. Consistent with ideological beliefs affecting investment opinions, I find that social media posters express more negative sentiment towards boycotted firms on X when they are ideologically aligned with the boycotters. This result is robust to including boycott fixed effects and controlling for other poster characteristics, suggesting that it is unlikely driven by other firm or poster characteristics. Content analysis of posts suggests that among all sample posts, 38% only mention the boycotted firm's financial prospects, 6% only make ideological identity-related statements, and 7% do both.[8] This suggests that while posts providing financial commentary are more prevalent overall, a small fraction of posts express opinions from the standpoint of ideological identity.

Turning to the main research question about whether ideology-driven social media opinions amplify negative market reaction to boycotts, I start by examining whether ideology-driven social media discourse is associated with stock returns following polarizing boycotts. First, I find that polarizing boycotts are associated with an approximate 1% (2.3%) drop in equity values over 7 (60) trading days after they start trending on X. The immediate market reaction is

[8] See Appendix E for examples of posts in each category.

more negative when a greater proportion of posts about boycotted firms originate from posters ideologically aligned with the boycotters, a pattern that also exists in retail investor trading. Path analysis indicates that this negative association operates indirectly through social media sentiment towards the boycotted firm. In cross-sectional analyses, I find that this negative association is concentrated in posts that attract online engagement, discuss the financial performance of the boycotted firms, and originate from users with large followings or a history of financial commentary. These results suggest that ideology-driven social media opinions about public companies could exacerbate the negative market response to polarizing boycotts, especially when they are visible, financially relevant, and trusted.

In the next set of tests, I find evidence that social media posters' ideological diversity, calculated as the inverse Herfindal index of their ideological leanings, is positively associated with abnormal trading volume following polarizing boycotts. I also find a similar association between poster ideological diversity and post-boycott abnormal return volatility. These results suggest that greater ideological diversity among social media posters is positively associated with elevated trading volume and excess volatility.

Finally, because Lee, Hutton, and Shu (2015) find that stock price declines resulting from product recalls dampen when firms respond on social media, I examine whether this mitigation effect can also occur during polarizing boycotts. I find that the most common firm response to boycotts is silence (41%), followed by offering explanations (33%). Less frequent responses include reversing the controversial policy (15%) or doubling down (11%). However, there is no significant evidence that market reaction to boycotts differs based on response types.

This paper contributes to both research and practice in several ways. First, it adds to the literature on how social media content shapes investor information processing (Lee et al., 2015;

Jia et al., 2020; Campbell et al., 2023) by finding evidence consistent with the ideological leanings of social media posters influencing investor responses to politically polarizing news. A related study by Cookson et al. (2020) examines whether divergent ideological beliefs of StockTwits users are associated with investor disagreement during the COVID-19 pandemic. My study takes a different angle by examining market reaction to polarizing boycotts targeting individual firms, which encompass a multitude of themes such as climate change, gun policy, and LGBTQ rights. My study also broadens the research on political leanings of financial information intermediaries (Rees and Twedt, 2022; Goldman et al., 2024) by extending it to social media posters, who have increasingly become a trusted source of financial information, particularly among younger investors (CFA Institute, 2024). Although this study focuses on boycotts, the findings likely apply to other polarizing events, such as CEO statements on political issues.

Second, this paper contributes to the literature on the benefits and costs of social media coverage of firms. While prior research highlights benefits of social media such as improving firm visibility and liquidity (Blankespoor et al., 2014; Rakowski et al., 2019), recent work points to potential downsides, including distorted price discovery, lower price efficiency, and increased toxicity (Jia et al., 2020; Campbell et al., 2023; Blankespoor et al., 2025). Building on this, I find that ideology-driven social media discourse can amplify negative market responses to boycotts, a form of corporate crisis, and that opinions from posters with conflicting ideological leanings are positively associated with return volatility. Given growing concern among practitioners and regulators that the open nature of social media may destabilize markets (PwC, 2017; Board of Governors of the Federal Reserve, 2021), these findings offer insight into how online discourse, especially when politically charged, can shape market outcomes.

2. Background and hypothesis development

2.1. Background on polarizing boycotts

The political science literature defines boycotts of businesses as consumers' deliberate avoidance of certain products with the aim of changing corporate practices (Stolle and Micheletti, 2013). Boycotts can happen when firms actively take a stance on polarizing issues or when their business decisions are interpreted as supporting one side of a debate.

As an example of the former, in the spring of 2023, brands like Bud Light and Target introduced marketing campaigns in support of the LGBTQ community, with Bud Light partnering with transgender influencer Dylan Mulvaney and Target releasing its Pride Month product line. In response, conservative public figures protested such actions, aiming to "make 'pride' toxic for brands".[9] Subsequently, both Anheuser-Busch InBev (AB InBev) and Target experienced declining stock prices and analyst downgrades.[10] As an example of the latter, following the January 6 attack on the U.S. Capitol, news reports revealed that Microsoft's Political Action Committee (MSPAC) had in the past donated to members of Congress who tried to delay the certification of the 2020 presidential election results.[11] This sparked a wave of boycotts targeting Microsoft, initiated by liberal stakeholders including some Microsoft employees. While Microsoft likely did not intend to support election denial efforts at the time of its political donations, it became associated with them due to subsequent political developments. This highlights the fact that boycotts can often arise not just from deliberate ideological stances but also from the reexamination of firms' past actions in a different political context.

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[9] See: https://x.com/MattWalshBlog/status/1661333191951613952
[10] See: https://www.cnbc.com/2023/05/10/hsbc-downgrades-ab-inbev-as-it-deals-with-a-bud-light-crisis-.html; https://www.cnbc.com/2023/06/01/jpmorgan-downgrades-target-as-concerns-for-the-retail-giant-mount.html
[11] See: https://www.cnbc.com/2021/01/22/microsoft-president-brad-smith-defends-mspac-to-employees.

Social media platforms today serve as central hubs where individuals discuss boycotts. As retired U.S. Supreme Court Justice Anthony Kennedy observed, "[t]hese websites [Facebook and Twitter] can provide perhaps the most powerful mechanisms available to a private citizen to make his or her voice heard."[12] Hashtags and viral posts can quickly elevate a boycott from a niche political action to a global phenomenon. Moreover, because social media discussions are often visible to a wide audience, including investors, they can have consequences for firms' public images and stock market performance. Using a diverse sample of 125 ideologically polarizing social media boycotts, my paper documents the stock market's reaction to boycotts, and how ideology-driven social media opinions can affect this reaction.

2.2. Ideology-driven social media opinions and market outcomes

An active community of social media users frequently discusss financial news and investment strategies on platforms such as StockTwits and X. This community can include investors, financial analysts, journalists, and others interested in disseminating financial information. Faced with ideologically polarizing boycotts, social media posters may develop divergent opinions about the boycotted firm for financial value or identity congruence-related reasons.

From a financial value perspective, social media echo chambers are known to selectively expose users to information sources that reinforce their prior beliefs (Cookson et al., 2023; Guest et al., 2023). Thus, due to bounded rationality and/or selective exposure, posters ideologically aligned with boycotters are more likely to consume partisan content that frames the boycott as credible and consequential, prompting more negative assessments of the boycotted firm, whereas nonpartisans and those ideologically opposed may be exposed to information to the contrary.

[12] *Packingham v. North Carolina*, 582 U.S. 98 (2017).

Even when exposed to the same information, posters with different political beliefs can interpret it differently due to confirmation bias. This is consistent with findings in the behavioral finance literature that liberals and conservatives interpret the same events differently, such as sea level rises (Bernstein et al., 2022), COVID (Cookson et al., 2020), and Trump's election (Meeuwis et al., 2022). During a boycott, posters may interpret boycotters' threats in a way that is consistent with their ideological beliefs. Those aligned with the boycotters may view the threats as credible and financially damaging, while those ideologically opposed may be more likely to dismiss them, leading to different assessments of the boycotted firm's risk and future performance.

The dynamic between ideological beliefs and poster sentiment can also be understood from the perspective of social identity theory, which posits that individuals tend to feel more (less) committed to an organization when their identities align (misalign) with that of the organization (Tajfel and Turner, 1986; McDonnell and Cobb, 2020). During politically polarizing boycotts, posters who share the prevailing ideological beliefs of the boycotts may feel less aligned with the boycotted firm and more motivated to express disapproval through negative commentary, while those who identify with the opposing side may express support or indifference.

Prior research in accounting and finance shows that investors obtain information from social media and that social media opinions can influence trading behavior. For example, Cookson and Niessner (2020), Jia et al. (2020), and Campbell et al. (2023) find that investment-related discussions on social media significantly shape market reactions to events such as earnings announcements and merger rumors. Building on this literature, I argue that social media can amplify market responses to boycotts that could be costly to firms and their shareholders. First, if investors rely on social media to guide their trading decisions, and if social media users interpret politically salient events through an ideological lens, then ideology-driven commentary may shape the price reaction to boycotts. However, it is also possible that investors perceive boycotts as financially inconsequential, or disregard ideology-driven social media discourse as economically irrelevant, leading to no relationship between ideology-driven opinions and price reaction. To the extent that such opinions do inform trading decisions, I expect that market reactions to politically polarizing boycotts will be more negative when a larger share of social media posts about the boycotted firm come from users who are ideologically aligned with boycotters. Based on this reasoning, I make the following prediction regarding post-boycott stock returns:

H1: The price response to an ideologically polarizing boycott is more negative when a higher fraction of social media posters is ideologically aligned with the boycotters.

Beyond price decline, another potentially costly market outcome for firms and their shareholders is excess return volatility. Theory suggests that when investors hold heterogeneous beliefs and agree to disagree, elevated disagreement is associated with both higher trading volume and greater return volatility (Scheinkman and Xiong, 2003; Banerjee and Kremer, 2010). If conflicting ideological beliefs among social media posters give rise to divergent investment opinions, and if investors incorporate this disagreement into their trading decisions, then social media discourse shaped by ideological conflicts may be linked to increased trading volume and excess volatility. This leads to my second prediction:

H2: Following an ideologically polarizing boycott, abnormal trading volume and abnormal realized volatility increases with the diversity of social media posters' ideological beliefs.

3. Data and sample construction

To identify social media boycotts, I start from daily top 50 trending topics on X archived by www.trendcalendar.com, and check if each one represents a boycott of public companies based on the matching procedure detailed in Appendix IA1. I identify 256 trending boycotts targeting 94 public companies in the CRSP database from April 2016 through October 2022.

After this initial step, I manually classify the boycotts into several categories based on the nature of the issues and classify their prevailing ideological beliefs as liberal or conservative (see detailed procedure in Appendix IA2). Out of this sample, I retain the 130 boycotts pertaining to corporate stances or actions regarding polarizing issues identified by the USC Polarization Index (USC Center for Public Relations, 2022), as I expect ideology to play a major role in how these boycotts are perceived and not the ones pertaining to non-polarizing issues.[13] The issue categories are Abortion, COVID-19, Climate Change, Domestic/International Politics, LGBTQ Rights, Gun Policy, and Racial Equality/Policing Policy. I also exclude boycotts targeting foreign ADRs, because their prices are primarily determined by the prices of underlying shares in their respective home markets. This further reduces the number of boycotts to 125. See Table 1 for sample selection procedure and Appendix A for a complete list of the boycotts in the final sample.

For each boycott, I use the Twitter Academic API to download posts containing boycotted firms' cashtags in the days following when these boycotts trended. I end up with 139,395 posts by 61,840 unique posters. After collecting this initial sample, I instruct the ChatGPT API (GPT-3.5-turbo) to filter out posts that are technical analyses or advertisements.[14] Released by OpenAI

[13] In addition, boycotts pertaining to non-polarizing issues, such as price hikes, gender equality, and corporate misconduct, often garner bipartisan support on X in terms of poster opinions. This complicates the process of determining the ideology of boycotters and often renders the concept of "posters ideologically aligned with/opposed to the boycotters" irrelevant.
[14] For this task, GPT-3.5-turbo is used instead of GPT-4 because the task is straightforward. To evaluate ChatGPT classifications, I classify 100 random posts as technical analysis/not technical analysis and ads/not ads. A

in November 2022, ChatGPT is a GLLM applicable to many natural language processing tasks. de Kok (2025) points out that GLLMs can be more easily adapted to complex tasks than other textual analysis methods, and they can be more consistent and efficient than research assistants.

After filtering out the technical analysis and advertisement posts identified by ChatGPT, I inspect the data to further exclude posts that only reference target firms' cashtags incidentally.[15] In addition, I also exclude posts outside the [0, +1] day window following when the boycotts trend. My final sample consists of 77,190 posts with control variable data, stemming from 125 boycotts targeting 58 firms. These posts are generated by 40,440 unique posters. A potential concern is that posts containing cashtags may have been made not by investment-focused users, but by people participating in the boycott. To reduce this concern, Panel A of Table IA1 presents the most common words in the profiles of posters in my sample, revealing a strong investment focus (e.g., "stocks," "crypto," "options," "investing"). Panel B contrasts the most frequent words in my sample (posts containing cashtags posted around boycotts) with those in posts containing boycott hashtags posted in the same time period.[16] The results indicate that while my sample posts primarily feature investment terms, generic posts around boycotts do not have such focus. This evidence suggests that the users in my sample are likely focused on investment-related discussions.

To explore the relation between ideology-driven social media opinions and market reaction to boycotts, I also obtain stock market variables from CRSP and TAQ, along with financial

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comparison of the manual classifications and ChatGPT classifications reveals that ChatGPT has an F1 score of 80% (85%) when identifying technical analyses (ads).

[15] Specifically, the posts I manually filtered out contain Hyatt's cashtag $H, as $H is sometimes used as part of math formula or an intentional misspelling of "SH".

[16] Note that I was only able to collect posts containing boycott-related hashtags for 93 (74%) of the boycotts in the sample before the Twitter Academic API was abruptly shut down in June 2023. However, there is no reason to believe the most frequent words in posts about these boycotts are not representative of the overall sample.

performance variables from Compustat, analyst following data from I/B/E/S, institutional ownership data from Thomson Reuters, and traditional news media data from RavenPack.

4. Research design and descriptive statistics

4.1. Measurement of social media poster ideology

Research in political science shows that the political ideology of social media users can be reliably determined by analyzing the political accounts they follow due to homophily in social networks. One of the pioneering studies, Barberá (2015) estimates Twitter posters' political ideology based on the partisan accounts they follow. To validate this approach, he links a sample of Twitter accounts to real-world voters and campaign posters, finding a strong correlation between Twitter-based ideology and party registration and likewise for campaign contribution. Applying the same method to classify Twitter user ideology, Halberstam and Knight (2016) show that posters who follow mostly liberal accounts post favorably about Democrats and unfavorably about Republicans, and vice versa, further validating the classification method.

Drawing on this well-established approach, I estimate social media poster ideology from the partisan accounts they follow. Compared to classifying poster ideology based on explicit partisan language in post histories (Cookson et al., 2020), this method has the advantage of directly capturing the potential partisan nature of posters' information sets. It can also identify the beliefs of posters who avoid using partisan language to appear as credible financial commentators. To begin, I collect the X accounts of U.S. federal and state and local politicians in office as of January 2023 from the following sources: ProPublica's Politiwoops project (https://projects.propublica.org/politwoops/), the UCSD Library website (https://ucsd.libguides.com/congresstwitter), the U.S. House of Representatives Press Gallery (https://pressgallery.house.gov/member-data/members-official-twitter-handles), and a list of

Cabinet Members' accounts compiled by @TwitterGov (https://x.com/i/lists/88345660). Because these sources do not include accounts belonging to politically biased media organizations, pundits, or former politicians, I further collect political accounts from the datasets shared by Wojcieszak et al. (2022) and Green (2018) and manually compile an additional 39 liberal pundit accounts and 39 conservative pundit accounts from various online sources. After this step, there are 1,036 liberal X accounts and 899 conservative X accounts. To ensure equal numbers of liberal and conservative accounts, I obtain the 137 most highly followed conservative X accounts that are followed by two prominent conservative organizations (@Heritage and @NRA), ending up with 1,036 liberal X accounts and 1,036 conservative X accounts. Finally, I match these 2,072 political accounts to each poster's X following list and compute the number of liberal and conservative accounts each poster follows. A poster is classified as a liberal if she follows more liberal accounts than conservative ones, as a conservative if the reverse is true, or as a nonpartisan if she follows no political accounts or an equal number of liberal and conservative accounts.

Next, I assess the validity of this measure of poster ideology using two approaches. First, following Cookson and Niessner's (2020) method of using distinct words to confirm meaningful differences between categories, Panel A of Table 2 lists the 15 most frequently used words in each poster group's profiles that do not appear in the profiles of other groups. The top words are clearly divided along party lines: liberals often use terms like "voteblue," "bidenharris," and "getvaccinated," whereas conservatives often use terms like "ultramaga," "draintheswamp," and "unvaxxed." Second, following Halberstam and Knight (2016), I correlate my ideology measure with 2020 presidential election results at the state level using posters' self-disclosed location data.[17] I find that across states, the share of posters classified as liberal (conservative) under my method and the share of 2020 Biden (Trump) voters are highly correlated, with a coefficient of 0.71 (0.76) significant at the 0.01 level. Figure IA1 further shows that when plotting each state's share of posters classified as liberals (conservatives) against its share of 2020 Biden (Trump) voters, most states align closely with the 45-degree line. These results suggest that my measure of ideology reasonably captures posters' political leanings.

4.2. Measurement of social media sentiment towards the boycotted firm

To proxy for social media sentiment towards boycotted firms, I measure the sentiment expressed towards boycotted firms in each post. Although the widely used Twitter RoBERTa-base model generates high-quality classifications of post-level sentiment (Loureiro et al., 2022), several features of the posts in my sample complicate the task. First, these posts often reference multiple stocks and other entities and express conflicting sentiment towards them. Thus, it is necessary to isolate the sentiment expressed towards specific firms mentioned in a post. Second, it is often challenging for sentiment classifiers to detect subtle sentiments such as sarcasm, which are prevalent in social media posts. For example, the following post subtly criticizes Pepsi: "what's the word for greenwashing but for 'empowering women'? $PEP @PepsiCo."[18] This post does not direct any overtly negative words towards Pepsi, yet it conveys the author's discontent. Finally, many posts contain words that convey positive or negative sentiment only in an investment context (e.g., "long", "short", "call", and "put"), but sentiment classifiers trained on a general social media corpus like Twitter RoBERTa-base tend to label them as neutral words.

[17] 15,021 (37%) of the 40,440 posters in my sample disclose their states of residency in profiles. 2020 U.S. presidential election results by state are obtained from https://www.presidency.ucsb.edu/statistics/elections/2020.
[18] See: https://x.com/Bruno_J_Navarro/status/1486346090253279236

To tackle these challenges, I utilize ChatGPT (GPT-4) to assess the sentiment in posts directed at boycotted firms. With its proven capabilities in advanced NLP tasks (OpenAI, 2023), GPT-4 is equipped to handle the sentiment analyses required for this study. I construct a prompt that instructs GPT-4 to classify a post's sentiment towards a boycotted firm as positive, neutral, or negative. See Appendix C, Panel A for the prompt, and Appendix D for example classification results. Throughout all analyses using ChatGPT, I set the temperature parameter to zero, ensuring that the classification results are replicable and nearly deterministic. After ChatGPT completes the sentiment classification, I draw a random sample of 500 posts and ask a research assistant to independently classify the sentiment directed at the boycotted firm in each post. Comparing model classifications to manual classifications, Panel A of Table IA2 shows that GPT-4 has an accuracy (F1 score) of 76% (72%), which is higher than Twitter RoBERTa-base model's 63% (59%), Loughran-McDonald dictionary's 55% (42%), and FinBERT's 24% (17%).[19] Panel B further shows that GPT-4 consistently performs the best across positive, neutral, and negative posts. These statistics confirm that GPT-4 is better equipped to understand entity-specific sentiment of posts compared to variants of the BERT model and a dictionary-based approach.

4.3. Descriptive analysis of ideologically polarizing social media boycotts

Table 2, Panel B displays descriptive statistics on the ideologically polarizing boycotts. 80 (64%) of these boycotts are consistent with liberal ideological beliefs, whereas 45 (36%) of the boycotts are consistent with conservative ideological beliefs.

Table 2, Panel C examines the events leading to boycotts, summarized through an analysis of news articles and social media posts from the weeks preceding the boycotts. Of the 125

[19] Accuracy is the proportion of all classifications that are correct. The significant underperformance of FinBERT compared to other methods could be because it was trained on corporate filings, analyst reports, and conference call transcripts (Huang et al., 2023), which have very different linguistic features than posts by average social media posters.

boycotts, 82 arose from firm decisions grouped into six subcategories, with the most frequent being product or operational decisions, human resources decisions, and political contributions or advocacy. 26 arose from current or former employee actions or statements, involving both executives and rank-and-file employees. The remaining 17 were prompted by external factors, such as political figures' remarks, firms' inaction on polarizing issues, or actions by subsidiaries and franchisees.

Table 2, Panel D shows descriptive statistics on the number of cashtag posts made during polarizing boycotts and their average sentiment. The mean (median) number of cashtag posts when a boycott trends on X is 618 (223). The average poster sentiment towards boycotted firms is slightly negative at -0.14. Among boycotts consistent with liberal (conservatives) ideological beliefs, those concerning LGBTQ rights (domestic/international politics) have the highest interest.

Finally, Table 2, Panel E shows descriptive statistics of poster characteristics. Of the 40,440 posters in my sample, 13,935 (34%) are classified as liberals, 18,513 (46%) are classified as conservatives, and 7,992 (20%) are classified as nonpartisans. The average (median) liberal poster follows 55 (17) liberal accounts and 6 (2) conservative accounts, whereas the average (median) conservative poster follows 5 (1) liberal accounts and 66 (24) conservative accounts. In terms of financial commentary experience, the average nonpartisan posts 2,684 cashtags over eight months, far exceeding the average liberals and conservatives' cashtag count (below 500). This statistic, combined with the fact that nonpartisans are also more likely to have a higher bot score, suggests that nonpartisan posters in my sample are more likely to be automated accounts primarily engaged in broadcasting investment news or trading signals.

5. Validation test – poster ideological beliefs and sentiment towards boycotted firms

5.1. Research design

I first validate the conjecture that ideological alignment between social media posters and boycotters is associated with sentiment towards the boycotted firm, using the following model:

$$SentTowardsFirm_{i,j,b,t} = \beta_0 + \beta_1 Aligned_{i,j,b,t} + \beta_2 Opposed_{i,j,b,t} + \sum \beta_k\, UserCharacteristics + \delta BoycottFE + \varepsilon_{i,j,b,t} \quad (1)$$

The dependent variable $SentTowardsFirm_{i,j,b,t}$ is a categorical variable that can take values -1 (negative), 0 (neutral), or 1 (positive) to indicate social media poster *i*'s sentiment towards firm *j* during boycott *b* on date *t*.[20] The variable $Aligned_{i,j,b,t}$ is an indicator variable that equals one if poster *i* is ideologically aligned with the boycotters in boycott *b* targeting firm *j*, and equals zero otherwise. A social media poster is considered aligned with boycotters if the poster is a liberal (conservative) and the boycott is consistent with liberal (conservative) ideological beliefs. The variable $Opposed_{i,j,b,t}$ is an indicator that equals one if poster *i* is ideologically opposed to the boycotters in boycott *b* targeting firm *j*, and equals zero otherwise. A poster is considered opposed to boycotters if the poster is a liberal (conservative) and the boycott is consistent with conservative (liberal) ideological beliefs. Note that nonpartisans are neither aligned with nor opposed to boycotters.

Control variables include the following poster characteristics that are potentially correlated with sentiment towards boycotted firms: age of the account; decile ranking of cumulative post count in the poster's post history; decile rankings of follower and following counts; verification

[20] Because the dependent variable is ordinal with three possible categories, an ordinal logit or ordinal probit model is theoretically more appropriate than OLS. However, estimating an ordered logit model with boycott fixed effects through the Stata package *feologit* results in numeric overflow due to the model's computational complexity. Considering Angrist and Pischke's (2009) conclusion that compared with nonlinear models, OLS is easier to implement on panel data and often produce comparable findings, I conduct all my analyses using OLS regression. To confirm the appropriateness of OLS, I estimate an ordinal logit model with firm-level control variables from equation (3), poster-level controls from equation (1), and no fixed effects through the Stata package *ologit*. The ordered logit regression results yield the same inferences as those in Table 4.

status.[21] Additionally, since posters' experience with financial commentary may influence their perceptions of stocks, I control for their financial commentary activity, measured by the decile rank of posters' total cashtag usage in the five months preceding and three months following each post. Finally, because the computer science literature documents that posts made by humans express more extreme sentiment than those by automated accounts (Dickerson et al., 2014), I control for whether the poster is likely automated (i.e., "bot"), using the Botometer API to calculate a "bot score" for each poster. I classify posters with bot scores higher than 4 out of 5 as likely bots.

I cluster standard errors at the firm level and at the poster level. I also include boycott fixed effects, so the regression coefficients are estimated from within-boycott variation. I expect β_1 (β_2) to be negative (positive). That is, compared with nonpartisans, boycotter-aligned (boycotter-opposed) posters express more negative (positive) sentiment towards the boycotted firm.

5.2. Descriptive statistics of regression variables

Table 3, Panel A presents the descriptive statistics of regression variables. These statistics are calculated at the post level, meaning that posters who contribute multiple posts appear multiple times, so they differ from the poster-level statistics in Panel E of Table 2. Of all posts in the sample, 42% are made by posters ideologically aligned with boycotters, and 30% are made by those ideologically opposed to boycotters. As of posting date, the average (median) poster has been on X for 5.54 (5) years, has 16,417 (506) followers, follows 1,445 (327) other posters, and

[21] Note that because of the limitation of the Twitter API, I could only access cumulative post count, follower count, following count, and verification status as of the date on which I downloaded the data in January 2023. When constructing regression variables, I use posters' January 2023 verification status to proxy for their verification status at the time of post posting. I impute posters' cumulative post counts, follower counts, and following counts at the time of the post posting proportional to the ratio of their account age at the time of the post posting to the age of their account as of January 2023. Results in Table 4 remains qualitatively the same if I use the January 2023 values instead of the imputed values as control variables.

has made a total of 93,218 (13,619) posts. Posters' financial commentary experience is highly skewed: the average (median) poster referenced 17,847 (269) cashtags in their posts within an eight-month window. Finally, 3% of posts are from verified accounts and 15% from likely bots.

5.3. Regression results

Table 4, Panel A presents the main results of examining whether ideological beliefs affect social media users' opinions about boycotted firms. In Column (1), where the full sample is used, the coefficient on *Aligned* is -0.096 and significant at the 1% level. This indicates that compared to posts by nonpartisan posters, posts by boycotter-aligned posters are more negative towards the boycotted firms. This result is robust to including boycott fixed effects and controlling for other poster characteristics, suggesting that it is unlikely driven by contemporaneous firm fundamentals or other observable poster characteristics. To further substantiate this finding, I repeat the regression using different subsamples. In Column (2) I present regression results excluding posts with more than five cashtags, because posts referencing many cashtags are likely to be auto-generated trading signals rather than personal investment opinions. To reduce concerns that the main results are not driven by investment-focused posters, I further exclude posters with below-median financial commentary experience in Column (3), or posters who do not self-describe as investment professionals in their profiles in Column (4). The results remain quantitatively similar to those in Column (1) under these alternative specifications. Excluding bot accounts from the analyses also yields similar findings (Table 4, Panel B.)

Interestingly, in Table 4, Panel A, the coefficient on *Opposed* is not significantly different from zero in any column, indicating no significant difference in sentiment between boycotter-opposed posters and nonpartisans. Boycotter-opposed posters' hesitation to voice support for the boycotted firm could stem from a fear of backlash, consistent with the spiral of silence theory

(Noelle-Neumann, 1974), which suggests that individuals are less likely to express their opinions when those opinions are unpopular within a group. Hence, during a polarizing boycott, it is possible that boycotter-opposed posters feel isolated due to the widespread outrage on X, leading them to withhold verbal support for the boycotted firms.

Overall, the results in Table 4, Panel A indicate that relative to nonpartisans, investment-focused social media users ideologically aligned with boycotters express more negative sentiment towards boycotted firms. In contrast, posters ideologically opposed to boycotters do not express more positive sentiment relative to nonpartisans, possibly due to a fear of backlash.

5.4. Content Analysis of Post Focuses

Having examined the sentiment of posts and its underlying drivers, I now turn to whether these posts discuss the financial performance of boycotted firms or make political statements. For this task, I use the ChatGPT API (GPT-4o) to identify whether each post in the sample assesses the financial performance of the boycotted firm, and whether it expresses ideological opinions.[22] See Appendix C, Panel B for the prompt, and Appendix E for example classification results. After ChatGPT completes the classification, I draw a random sample of 500 posts and ask a research assistant to independently classify the focus of each post. Comparing model classifications to manual classifications, I find that ChatGPT has an accuracy (F1 score) of 79% (78%) when identifying posts referencing boycotted firms' financial performances, and an accuracy (F1 score) of 95% (81%) when identifying posts referencing political ideology.

Content analysis suggests that 38% of posts only mention the boycotted firm's financial performances, 6% only make ideological identity-related statements, 7% do both, and 49% do

[22] Identifying financial and ideological language requires more nuanced judgment than sentiment classification. For this task, I use the GPT-4o model, which outperforms GPT-4 on tasks involving complex language interpretation.

neither.[23] In particular, among posts by users ideologically aligned with boycotters, 38% only mention financial performances, 9% only make ideological statements, and 10% do both. These patterns suggest that while financial commentary posts are more prevalent overall, ideological expressions are slightly more prevalent among posters ideologically aligned with boycotters.

6. Social media poster ideology and stock market responses to boycotts

6.1. Descriptive statistics on market reaction to polarizing boycotts

As a starting point for exploring stock market responses to polarizing boycotts, I analyze stock returns around boycotts and their cross-sectional variation.

First, in descriptive analyses presented in Panel A of Table 5, I find modest evidence of negative market-adjusted buy-and-hold abnormal returns (*BHAR*s) immediately after the boycotts start to trend on X, and no significant evidence of negative reaction beforehand. Two-tailed t-tests indicate that the mean *BHAR* is significantly negative at the 10% level for the [0, +1] and [0, +7] day windows. Signed rank tests indicate that median *BHAR* is significantly negative at the 5% level for the [0, +1] day window. Moreover, Figure 1 displays the mean and 90% confidence interval for buy-and-hold abnormal returns over the [-1, +60] trading days around when a boycott trends on X. The figure shows that polarizing boycotts are associated with an approximate 2.3% decline in equity value from day 0 to day 60, with no sign of reversal in this period, indicating that these boycotts can have a lasting negative effect on equity value.

To understand the cross-sectional variation in market reaction to boycotts, I partition the sample based on whether online posters are highly ideologically aligned with the boycotters. High ideological alignment is defined as cases where at least 50% of social media posters are

[23] Note that posts with no explicit references to either financial performance or political beliefs can still convey information relevant to investors. For instance, the following sample post related to Exxon Mobil ($XOM) reveals the poster's share purchase but does not explicitly assess the firm's financial conditions: "@DrDividend47 Today I add to the shares I do have $BAC $XOM $EQT $RBLX" (https://x.com/clpirtle25/status/1518681123794173952).

ideologically aligned with boycotters. Panel B of Table 5 presents evidence suggesting stronger immediate market reactions to boycotts when online posters are highly ideologically aligned with the boycotters, although the differences are not statistically significant.

6.2. Ideology-driven social media opinions and post-boycott returns

To directly examine H1, I estimate the following regression equation:

$$BHAR_b = \beta_0 + \beta_1 PctPosterAligned_b + \sum \beta_k\, Controls + \mu DayofWeekFE + \delta YearFE + \varepsilon_b \quad (2)$$

where subscript b indexes boycotts. The dependent variable $BHAR_b$ is the market-adjusted buy-and-hold abnormal return following boycott b, measured over three windows. The independent variable $PctPosterAligned_b$ is the percentage of posters ideologically aligned with boycotters out of all posters referencing the boycotted firm's cashtag. Control variables are boycotter ideology; total number of cashtags; firm size; book-to-market ratio; profitability; analyst following; institutional ownership; extent of traditional media coverage; and the average and standard deviation of traditional media sentiment.[24] I include day-of-the-week and year fixed effects and cluster standard errors by firm.[25] I predict β_1 to be negative, consistent with a higher proportion of boycotter-aligned posters being associated with more negative market reaction to boycotts.

Table 3, Panel B presents boycott-level descriptive statistics on the regression variables. As of the time of the boycott, an average sample firm has a market value of $47 billion, a book to

[24] Total number of cashtags posted in the [0, +1] window is included to controls for the magnitude of social media attention during the boycott. Untabulated analyses suggest that the results in Tables 6 and 8 are robust to excluding the 12 boycotts that attracted the most attention (highest cashtag counts).

[25] Untabulated analyses show the results in Tables 6 and 8 are broadly consistent when fixed effects are excluded. Exceptions include: in Table 6, Panel A, the coefficient on *PctPosterAligned* in Column 1 becomes insignificant, while in Column 2 it becomes significant at the 1% instead of 5% level. In Table 8, Panel A, the coefficients on *IdeoDiversityScore* in Columns 2 and 3 become significant at the 5% instead of 1% level. In Panel B, Column 2, the coefficient becomes significant at the 10% instead of 5% level, and in Panel C, Column 2, it is no longer significant.

market ratio of 0.46, and a return on assets of 0.02. Compared with the average Compustat firm-quarter in the same period, which has a market value of $5 billion, a book to market ratio of 2.43, and a return on assets of -0.02, my sample firms have higher market valuations, lower book-to-market ratio, and greater profitability.

Table 6, Panel A reports the results from estimating equation (2). The coefficient on *PctPosterAligned* is negative and statistically significant at the 10% level in Column (1) and the 5% level in Columns (2) and (3) in a one-tailed test, indicating that a higher percentage of opinions coming from boycotter-aligned posters is associated with more negative market reaction to boycotts. This negative relationship suggests that the ideological beliefs of social media posters can influence market responses to polarizing boycotts.[26] Specifically, as the proportion of boycotter-aligned posters increases, overall social media sentiment toward the boycotted firms becomes more negative, prompting investors who monitor social media to trade accordingly. This finding demonstrates the capital market implications of ideology-driven social media content.

6.3. The mediating role of overall social media sentiment towards boycotted firms

To explore whether the relation between *PctPosterAligned* and *BHAR* is mediated by overall social media sentiment towards target firms, in a path analysis, I break down the total effect of *PctPosterAligned* on market reaction into direct and indirect effects (Hayes, 2018):

$$AvgSentTowardsFirm = \alpha_1 + \beta_1 PctPosterAligned_b + \sum \theta_k\, Controls + \mu_1 DayofWeekFE + \delta_1 YearFE + \varepsilon_{i1} \quad (3)$$

$$BHAR = \alpha_2 + \beta_2 PctPosterAligned_b + \gamma AvgSentTowardsFirm_b + \sum \pi_k\, Controls + \mu_2 DayofWeekFE + \delta_2 YearFE + \varepsilon_{i2} \quad (4)$$

[26] One concern here is that the market reaction to boycotts is confounded by other prior events such as media articles and earnings announcements. To alleviate this concern, untabulated analyses show that the results in Tables 6 and 8 are robust to controlling for the extent and sentiment of news coverage in the [-7, -1] window. In addition, Figure IA2 plots a histogram of the distribution of boycott trending dates relative to the closest earnings announcement dates. The trending dates do not cluster around or away from earnings announcement dates. Further, only about 6% of boycotts started trending in the [-5, +5] day window around earnings announcements.

Here, *AvgSentTowardsFirm* is the average sentiment of posts referencing the boycotted firm's cashtag, measured over the day on which the boycott first trends on X and the day after. Control variables are the same as those in Table 6, Panel A. β_2 represents the direct effect of *PctPosterAligned* on market reaction, $\beta_1\gamma$ represents the indirect effect of *PctPosterAligned* on market reaction via *AvgSentTowardsFirm*, and $\beta_2 + \beta_1\gamma$ represents the total effect of *PctPosterAligned* on market reaction. I expect the total effect and indirect effect of *PctPosterAligned* on market reaction to boycotts to be negative.

Table 6, Panel B reports the result of estimating this system of equations (see Figure 2 for a graphic representation of the results). The total effect of *PctPosterAligned* on market reaction and its significance level mirror the coefficients on *PctPosterAligned* in Panel A. The direct effect of *PctPosterAligned* on market reaction has mixed signs and is not close to being significant. The indirect effect of *PctPosterAligned* on market reaction via *AvgSentTowardsFirm* is negative and significant at the 5% level in Column (2) and approaches marginal significance in Columns (1) and (3). A percentage breakdown of the total effect shows that it is attributable to the indirect path. Taken together, the path analysis suggests that the negative association between the percentage of boycotter-aligned posters and market reaction to boycotts likely operates through average social media sentiment towards the boycotted firm. Importantly, this analysis does not establish causality. Rather, it suggests that a plausible channel through which higher *PctPosterAligned* can lead to more negative market reactions to boycotts is via more negative overall social media sentiment.

6.4. Cross-sectional variation in the relation between ideology-driven social media opinions and post-boycott returns

Next, I explore cross-sectional variation in the relationship between *PctPosterAligned* and market reaction to boycotts by partitioning *PctPosterAligned* based on post and poster characteristics. For each characteristic, I partition *PctPosterAligned* into mutually exclusive subcomponents that sum to the original variable.[27] Post-level factors include visibility (number of likes, retweets, and replies), other factors associated with post visibility (hyperlinks and repost status), and content focus (financial value vs. ideological identity). Poster-level factors include social media influence (follower count) and financial commentary experience (cashtag activity). See Appendix B for detailed variable definitions.

First, I test whether the relationship is stronger for high-visibility posts. If ideology-driven opinions move markets, the effect should be concentrated within posts with higher engagement. Results in Table 7, Panel A show that the coefficient on *PctPosterAligned_PosImp* (posts with at least one like, retweet, or reply) is negative and significant at the 1% or 5% level in all specifications, whereas the coefficient on *PctPosterAligned_ZeroImp* (posts with no like, retweet, or reply) is not significant. This suggests that the relationship between *PctPosterAligned* and market reaction is concentrated among posts with some online engagement.

Second, I examine two additional factors associated with the visibility of posts: presence of hyperlinks and repost status. Prior research consistently shows that posts without hyperlinks receive higher engagement, likely because of algorithmic biases and lower effort required from readers (e.g., Engelmann et al., 2019; Sehl and Martin, 2021). For reposts, the fact that a post is being reshared implies it has already begun to reach an audience. Panels B and C show that the association between *PctPosterAligned* and market reaction is concentrated in posts without

[27] For example, if 30% of posts related to a given boycott come from posters ideologically aligned with the boycotters, and half of these posts receive at least one like, retweet, or reply while the other half receive none, then *PctPosterAligned* = 30%, with *PctPosterAligned_PosImp* = 15% and *PctPosterAligned_ZeroImp* = 15%.

hyperlinks (*PctPosterAligned_NoLink*) and those that are reposts (*PctPosterAligned_Repost*). Taken together with results in Panel A, this suggests that ideology-driven social media posts matter more when they are more easily processed and widely disseminated.

Third, I examine whether the focus of posts matters. Table 7, Panel D shows that posts discussing financial performance, either alone (*PctPosterAligned_FinOnly*) or alongside ideological opinions (*PctPosterAligned_Both*), are negatively and significantly associated with market reaction to boycotts. In contrast, posts that discuss neither financial performance nor ideological stances (*PctPosterAligned_Neither*) are occasionally significantly associated with returns (Column 1), whereas posts that only state political opinions (*PctPosterAligned_IdeoOnly*) are never significant. These findings suggest that the relationship between *PctPosterAligned* and market reaction is mostly concentrated in posts of economic substance.

Finally, I evaluate the role of poster characteristics. Results in Panels E and F respectively show that the relationship between *PctPosterAligned* and market reaction to boycotts is mostly attributed to posters with above-median follower counts (*PctPosterAligned_HiInf*) and those with above-median eight-month cashtag counts (*PctPosterAligned_HiExp*). This suggests that ideology-driven opinions are most impactful when they come from influential users and experienced financial commentators.

Together, these results show that the relationship between ideology-driven social media activity and market reaction to boycotts is not uniform. It is primarily attributed to posts that attract engagement, emphasize financial implications, and originate from influential, prolific users. Because the differences in coefficients have mixed significance, the cross-sectional results are suggestive, rather than conclusive, evidence of which posts and posters drive the results.

6.5. The role of the boycotted firm's perceived political ideology

The paper so far has been silent on whether market reaction to boycotts differs based on boycotted firms' perceived ideology. In this section, I examine whether the perceived ideology of boycotted firms moderates market responses to boycotts. I interpret a firm's ideology to be the ideology of employees, following Mkrtchyan et al. (2023) which examines how stakeholder ideology affects market responses to CEO activism statements. I compute the average ideological leaning of employees by weighting each firm's locations according to the number of employees at each site.[28] Figure 3 shows that the negative market reaction to boycotts is primarily driven by boycotts where the majority of employees are ideologically aligned with boycotters. That is, the market seems to expect the consequences of boycotts to be more negative when the firm is perceived as ideologically aligned with boycotters, possibly due to lower employee productivity.

7. Ideological diversity and investor disagreement following polarizing boycotts

In this section, I examine whether post-boycott trading volume and return volatility increases with the diversity of poster ideology, as proposed in H2. I estimate the following equation:

$$Outcome_b = \beta_0 + \beta_1 IdeoDiversityScore_b + \sum \beta_k \, Controls + \mu DayofWeekFE + \delta YearFE + \varepsilon_b \quad (5)$$

Where subscript *b* indexes boycotts. The outcomes I examine include abnormal shares turnover (*AbTurn*), abnormal daily return volatility (*AbVola*), and abnormal intraday return volatility (*AbIVola*). The independent variable (*IdeoDiversityScore*), adapted from country origins

[28] Specifically, using the approach of Mkrtchyan et al. (2023), I classify employees working at a firm's headquarters as liberal or conservative based on the most recent presidential election results in the county where the headquarter is located: liberal if the Democratic candidate won and conservative if the Republican candidate won. For employees not working at the headquarters, I classify them similarly based on whether the Democratic or Republican candidate won the state where their work location is. The number of employees at each location is sourced from Infogroup.

diversity measure in Zhang et al. (2010), is the inverse Herfindahl index of poster ideological diversity:

$$IdeoDiversityScore = \frac{1}{PctInvestorAligned^2 + PctInvestorNeutral^2 + PctInvestorOpposed^2} \quad (6)$$

Because a higher Herfindahl index indicates *less* diversity, a higher *IdeoDiversityScore* indicates *more* diversity in posters' ideological beliefs. For example, a boycott with an even split of aligned, nonpartisan, and opposed posters would have an *IdeoDiversityScore* of 3, higher than that of a boycott with only boycotter-opposed posters (*IdeoDiversityScore* = 1). Control variables are the same as those in Equation (2). I also include day-of-the-week and year fixed effects, and cluster standard errors by firm. I predict β_1 to be positive, meaning that post-boycott shares turnover and return volatility increases with the diversity of poster ideology.

Table 8, Panel A presents regression results with average abnormal shares turnover over trading days [0, +*t*] as the depend variable, where day 0 marks the day on which boycotts start to trend on X and *t* equals 1, 3, or 7. Consistent with H2, the coefficient on *IdeoDiversityScore* is positive and significant at the 1% level in all columns. Moving from the first to the third quartile of *IdeoDiversityScore* is associated with 0.19% (122% of the mean abnormal turnover) greater four-day abnormal turnover. For control variables, liberal boycotts, more cashtag discussions, smaller firms, less analyst following, more negative and dispersed media sentiment, and more media coverage are associated with higher abnormal turnover.

In Panel B where the dependent variable is abnormal daily return volatility, the coefficient on *IdeoDiversityScore* is positive and significant at the 5% level in both columns.[29] Moving from

[29] I do not include results for the [0, +1] trading window in Panel B, because it is not particularly meaningful to consider the standard deviation of stock returns over two days.

the first to the third quartile of *IdeoDiversityScore* is associated with 0.34% (six times the mean abnormal daily return volatility) greater post-boycott four-day abnormal daily return volatility. In Panel C where the dependent variable is abnormal intraday return volatility, the coefficient on *IdeoDiversityScore* is positive and marginally significant in Column (2) and approaches marginal significance in Column (3). Moving from the first to the third quartile of *IdeoDiversityScore* is associated with 2.26% (almost equal to the mean abnormal intraday return volatility) greater post-boycott four-day abnormal intraday return volatility.

Taken together, the regression results in Table 8 suggest that both trading volume and return volatility following polarizing boycotts increase with diversity of social media posters' ideological beliefs, supporting H2. The link between conflicting ideological stances on social media and increased return volatility may be a concern for both the boycotted firms and their shareholders. Importantly, this does not necessarily indicate a causal relationship. It is possible that boycotts stemming from polarizing issues are associated with both high volatility and posters with diverse ideological beliefs speaking out on X. In this case, *IdeoDiversityScore* is a useful metric for gauging disagreement around the impact of a polarizing boycott.

8. Additional tests

8.1. Alternative cutoffs for social media poster ideology

To test whether the results in Table 4, Panel A are robust to alternative cutoffs of number of political accounts followed, I redefine partisan (nonpartisan) posters as those with a high (low) relative ideology difference score, calculated as follows:

$$RelIdeoDiffScore = \frac{|\#\ of\ liberal\ accounts\ followed - \#\ of\ conservative\ accounts\ followed|}{(\#\ of\ liberal\ accounts\ followed + \#\ of\ conservative\ accounts\ followed)/2} \quad (7)$$

In Table 9, Panel A, I define liberals (conservatives) as those who follow more liberal (conservative) accounts *and* have a relative ideology difference score above 0.3, effectively requiring higher thresholds for a poster to qualify as a liberal or a conservative. Regression results show that the findings in Table 4, Panel A are robust to the alternative cutoff.

8.2. Capital market tests focused on retail investors

Since boycotts are often started by grassroot individuals or organizations, I specifically examine how *retail* investors react to these events likely initiated by their peers, and whether this response is associated with ideology-driven social media commentary. Specifically, I test H1 by examining the relation between abnormal retail order imbalance and *PctPosterAligned* and H2 by examining the relation between abnormal retail shares turnover and *IdeoDiversityScore.* Following suggestions by Barber et al. (2024), I use the Boehmer et al. (2021) algorithm to *identify* retail trades, and the Lee and Ready (1991) quote midpoint signing method to *classify* these trades as buys and sells, using code adapted from Blankespoor et al. (2019).

Table 9, Panel B shows the result of testing H1 among retail investors. The association between abnormal retail order imbalance and *PctPosterAligned* is consistently negative across all specifications and statistically significant in Columns (2) and (3), where the dependent variable is volume-based abnormal retail order imbalance. Panel C presents the result of testing H2. The association between abnormal retail shares turnover and *IdeoDiversityScore* is insignificant. Overall, results in Table 8 are consistent with H1 but inconsistent with H2. This might indicate that retail investors only pay attention to social media posts by those ideologically aligned with boycotters. However, caution is warranted when interpreting these findings. First, Barber et al. (2024) demonstrate that the Boehmer et al. (2021) algorithm successfully identifies only 20% to 50% of retail trades. Second, the power of my tests may be low due to the small sample size.

8.3.Firm responses to polarizing boycotts

Finally, because Lee, Hutton, and Shu (2015) show that corporate social media responses can dampen product recall-related price declines, I examine whether the same mitigation effect occurs during polarizing boycotts. Accordingly, Panel D of Table 9 compares post-boycott returns across alternative firm responses. I collected firm response data by reviewing news articles and social media posts published in the weeks following each boycott. The most common response is to remain silent, observed in 51 cases (40%). In 41 cases (34%), firms issue an explanation or add context. Nineteen firms (15%) reverse their polarizing positions, while 14 firms (11%) double down or refuse to reverse their stance. Because firms take, on average, a little less than three days to respond after a boycott begins trending, I compare post-boycott returns over the [0, +3] and [0, +7] windows across different response types. I find no significant differences in returns between firms that provide an explanation, reverse the policy, or double down, compared to those that remain silent. However, given the small subsample sizes and the possibility that the severity of boycotts can determine both firm responses and market reaction, these findings are not conclusive evidence that firm responses to boycotts have no impact on post-boycott returns.

9. Conclusion

Using 125 polarizing boycotts, this study examines whether ideology-driven social media opinions affect market responses to polarizing boycotts. I find that posters express more negative sentiment towards the boycotted firm when they are ideologically aligned with boycotters. For market outcomes, the market reaction to boycotts is negative on average, and more so when posters ideologically aligned with boycotters dominate the social media discourse. This relationship is concentrated among posts that are visible, financially relevant, and trusted.

Finally, there is moderate evidence that post-boycott return volatility increases with the diversity of social media posters' ideological beliefs. Collectively, the findings show that ideology-driven social media opinions could amplify negative market consequences of polarizing boycotts.

This study is among the first large-sample investigations to examine the capital market consequences of ideologically polarizing boycotts. In an era where investors increasingly turn to social media for financial information, the findings extend our understanding of how the ideological leanings of financial information intermediaries can shape market outcomes, not only through traditional media, but also through social media. The evidence indicates that ideology-driven social media commentary around boycotts amplifies price declines and heightens volatility, highlighting the costs social media activities can impose on firms and shareholders in a crisis. Finally, the study showcases a novel application of generative AI in textual analysis.

I acknowledge two caveats. First, given this paper's cross-sectional design, I do not claim that the relation between ideology-driven social media discussions and market outcomes is causal. I reduce endogeneity concerns by including an extensive set of control variables, implementing a path analysis to identify the mechanism through which the relation occurs, and using cross-sectional tests to show that this relation varies with post and poster attributes. Second, because this paper focuses on polarizing boycotts, which are inherently ideologically salient, I cannot speak to whether ideology-driven social media discourse also affects how investors respond to less ideologically salient information events such as earnings announcements.

References

Angrist, J.D. and Pischke, J.S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Banerjee, S. and Kremer, I. (2010). Disagreement and learning: Dynamic patterns of trade. *The Journal of Finance*, *65*(4), 1269-1302.

Barber, B. M., Huang, X., Jorion, P., Odean, T., & Schwarz, C. (2024). A (sub) penny for your thoughts: Tracking retail investor activity in TAQ. *The Journal of Finance*, *79*(4), 2403-2427.

Barberá, P. (2015) Birds of the same feather post together: Bayesian ideal point estimation using Twitter data. *Political analysis*, *23*(1), 76-91.

Bartov, E., Faurel, L. and Mohanram, P.S. (2018). Can Twitter help predict firm-level earnings and stock returns?. *The Accounting Review*, *93*(3), 25-57.

Bernstein, A., Billings, S.B., Gustafson, M.T. and Lewis, R. (2022). Partisan residential sorting on climate change risk. *Journal of Financial Economics*, *146*(3), 989-1015.

Blankespoor, E., deHaan, E., Wertz, J., & Zhu, C. (2019). Why do individual investors disregard accounting information? The roles of information awareness and acquisition costs. *Journal of Accounting Research, 57*(1), 53-84.

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*(1), 79-112.

Blankespoor, E., Pinto, J. and Sinha, K. (2025). Social Media Toxicity and Capital Markets. *Available at SSRN 4692457*.

Boehmer, E., Jones, C.M., Zhang, X. and Zhang, X. (2021). Tracking retail investor activity. *The Journal of Finance*, *76*(5), 2249-2305.

Board of Governors of the Federal Reserve System (2021). Financial Stability Report. https://www.federalreserve.gov/publications/files/financial-stability-report-20211108.pdf

Campbell, B., Drake, M., Thornock, J. and Twedt, B. (2023). Earnings virality. *Journal of Accounting and Economics*, *75*(1), 101517.

CFA Institute (2024). The Finfluencer Appeal: Investing in the Age of Social Media. https://rpc.cfainstitute.org/sites/default/files/-/media/documents/article/industry-research/finfluencer-report.pdf

Chavis, L., & Leslie, P. (2009). Consumer boycotts: The impact of the Iraq war on French wine sales in the US. *Quantitative Marketing and Economics*, *7*, 37-67.

Cookson, J.A., Engelberg, J.E. and Mullins, W. (2020). Does partisanship shape investor beliefs? Evidence from the COVID-19 pandemic. *The Review of Asset Pricing Studies*, *10*(4), 863-893.

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

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

de Kok, T. (2025). ChatGPT for textual analysis? How to use generative LLMs in accounting research. *Management Science*.

Dickerson, J. P., Kagan, V., & Subrahmanian, V. S. (2014, August). Using sentiment to detect bots on twitter: Are humans more opinionated than bots?. In *2014 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM 2014)* (pp. 620-627). IEEE.

Engelmann, I., Kloss, A., Neuberger, C., & Brockmann, T. (2019). Visibility through information sharing: The role of tweet authors and communication styles in retweeting political information on Twitter. *International Journal of Communication*, *13*, 20.

Goldman, E., Gupta, N. and Israelsen, R. (2024). Political polarization in financial news. *Journal of Financial Economics*, *155*, 103816.

Green, J. (2019). Identifying and estimating the ideologies of Twitter pundits. *Data for Progress*. https://www.dataforprogress.org/blog/2018/11/19/identifying-and-estimating-the-ideologies-of-twitter-pundits

Guest, N.M., Twedt, B.J. and Murren Vosse, M. (2023). Institutional investors and echo chambers: Evidence from social media connections and political ideologies. *Available at SSRN*.

Halberstam, Y. and Knight, B. (2016). Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter. *Journal of Public Economics*, *143*, 73-88.

Hayes, A. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 2nd edition. New York, NY: The Guildford Press.

Huang, A.H., Wang, H. and Yang, Y. (2023). FinBERT: A large language model for extracting information from financial text. *Contemporary Accounting Research*, *40*(2), 806-841.

Jia, W., Redigolo, G., Shu, S. and Zhao, J. (2020). Can social media distort price discovery? Evidence from merger rumors. *Journal of Accounting and Economics*, *70*(1), 101334.

Jin, H., Merkley, K., Sharma, A. and Ton, K. (2024). Customers' response to firms' disclosure of social stances: evidence from voting reform laws. *Review of Accounting Studies*, 1-45.

Kempf, E., Luo, M., Schäfer, L. and Tsoutsoura, M. (2023). Political ideology and international capital allocation. *Journal of Financial Economics*, *148*(2), 150-173.

Lee, C.M. and Ready, M.J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, *46*(2), 733-746.

Lee, L.F., Hutton, A.P. and Shu, S. (2015). The role of social media in the capital market: Evidence from consumer product recalls. *Journal of Accounting Research*, *53*(2), 367-404.

Liaukonytė, J., Tuchman, A. and Zhu, X. (2023). Frontiers: Spilling the beans on political consumerism: Do social media boycotts and buycotts translate to real sales impact?. *Marketing Science*, *42*(1), 11-25.

Loughran, T. and McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35-65.

Loureiro, D., Barbieri, F., Neves, L., Anke, L.E. and Camacho-Collados, J. (2022). TimeLMs: Diachronic language models from X. *arXiv preprint arXiv:2202.03829*.

McDonnell, M.H. and Cobb, J.A.(2020). Take a stand or keep your seat: Board turnover after social boycott boycotts. *Academy of Management Journal*, *63*(4), 1028-1053.

Meeuwis, M., Parker, J.A., Schoar, A. and Simester, D. (2022). Belief disagreement and portfolio choice. *The Journal of Finance*, *77*(6), 3191-3247.

Mkrtchyan, A., Sandvik, J. and Zhu, V.Z. (2024). CEO activism and firm value. *Management Science*, *70*(10), 6519-6549.

Noelle-Neumann, E. (1974). The spiral of silence: a theory of public opinion. *Journal of Communication*, *24*(2), 43-51.

OpenAI. (2023). GPT-4 technical report. *arXiv preprint arXiv:2005.14165*.

PwC (2017). Social media governance: Managing social media risk. https://www.pwc.com/m1/en/services/assurance/risk-assurance/social-media-governance/documents/social-media-governance.pdf

Rakowski, D., Shirley, S. E., & Stark, J. R. (2021). Twitter activity, investor attention, and the diffusion of information. *Financial Management*, *50*(1), 3-46.

Rees, L. and Twedt, B.J. (2022). Political Bias in the Media's Coverage of Firms' Earnings Announcements. *The Accounting Review*, *97*(1), 389-411.

Scheinkman, J.A. and Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of political Economy*, *111*(6), 1183-1220.

Sehl, K., & Martin, N. (2021). Experiment: Do tweets with links get less engagement and less reach? *Hootsuite Blog*. https://blog.hootsuite.com/linkless-tweets-experiment/

Stolle, D., & Micheletti, M. (2013). *Political consumerism: Global responsibility in action*. Cambridge University Press.

Tajfel H. and Turner J. (1986). The Social Identity Theory of Inter-Group Behavior. *Psychology of Intergroup Relations*, 7-24.

USC Center for Public Relations. (2022). The Polarization Index. *Previously available at: https://thepolarizationindex.com/* [URL no longer available as of 24 April 2024].

Wang, K. and Lu, S., 2022. Corporate political positioning and sales: Evidence from a natural experiment. *Available at SSRN 4084106*.

Wojcieszak, M., Casas, A., Yu, X., Nagler, J. and Tucker, J.A. (2022). Most posters do not follow political elites on Twitter; those who do show overwhelming preferences for ideological congruity. *Science Advances*, *8*(39), eabn9418.

Zhang, Y., Li, H., Li, Y. and Zhou, L.A. (2010). FDI spillovers in an emerging market: the role of foreign firms' country origin diversity and domestic firms' absorptive capacity. *Strategic Management Journal, 31*(9), 969-989.

Appendix A: Complete List of Polarizing Boycotts in the Sample

Category	Issuer Name	Trending Topic
Abortion	C V S Health Corp	#BoycottCVS-08/15/2019
	Lyft Inc	Lyft-09/04/2021
	Meta Platforms Inc	#DeleteFacebook-08/09/2022
	Walgreens Boots Alliance Inc	Walgreens-07/17/2022
Climate change	Exxon Mobil Corp	#ExxonKnew-09/14/2016
		Exxon-10/05/2020
COVID-19	Costco Wholesale Corp	#boycottcostco-05/08/2020
	Delta Air Lines Inc	Delta-04/19/2022
		Delta Air Lines-08/25/2021
		Delta CEO-12/28/2021
	Facebook Inc	#DeleteFacebook-07/17/2021
	Fox Corp	#FoxHatesAmericans-04/27/2021
		#FoxNewsLiedAsPeopleDied-04/04/2020
		#FoxNewsLies-03/18/2020
		Fox's Fake News Contagion-04/01/2020
	GameStop Corp	GameStop-03/19/2020
	Kroger Company	Kroger-12/14/2021
	Live Nation Entertainment Inc	Ticketmaster-11/11/2020
	Pfizer Inc	Pfizer-10/12/2022
	Sinclair Broadcast Group Inc	Sinclair-07/25/2020
	Southwest Airlines Co	Southwest-10/11/2021
	Spotify Technology S A	Spotify-01/25/2022
	Starbucks Corp	#BoycottStarbucks-01/19/2022
	United Airlines Holdings Inc	United Airlines-08/06/2021
		United Airlines-09/29/2021
	Walmart Inc	#BoycottWalmart-01/25/2022
Domestic / international politics	A T & T Inc	AT&T CEO-05/11/2018
	Activision Blizzard Inc	Blizzard-10/08/2019
	Aetna Inc	Aetna CEO-02/15/2017
	Allstate Corp	Allstate-03/03/2022
	Amazon Com Inc	Whole Foods-08/13/2022
	Coca Cola Co	#BoycottCocaCola-03/04/2022
		#BoycottCocaColaCo-03/27/2021
		#BoycottCoke-03/13/2021
	Comcast Corp	#BoycottNBC-10/14/2020
		Concast-03/20/2020
		MSNBC-04/01/2022
	Darden Restaurants Inc	#BoycottOliveGarden-08/25/2019
	Delta Air Lines Inc	Delta-03/31/2021
	Deutsche Bank A G	Deutsche Bank-03/19/2019
		Deutsche Bank-04/04/2022
		Deutsche Bank-06/29/2018
		Deutsche Bank-08/27/2019
	Dine Brands Global Inc	Applebees-02/24/2022
	Disney Walt Co	#BoycottABC-09/13/2019
		#BoycottMulan-08/16/2019
		Hulu-07/26/2022
	Exxon Mobil Corp	Exxon CEO-12/10/2016
	Facebook Inc	#DeleteFacebook-05/05/2021
		#DeleteFacebook-05/25/2019
		#DeleteFacebook-05/28/2020
		#DeleteFacebook-08/28/2020
		#DeleteFacebook-10/14/2019
		#DeleteFacebookNow-06/02/2020
		Facebook-10/14/2020
	Fox Corp	#CancelFox-03/12/2021
		Fox News-06/07/2022
	Goodyear Tire & Rubber Co	Goodyear-08/19/2020
	Grubhub Inc	Grubhub CEO-11/11/2016
	Home Depot Inc	#BoycottHomeDepot-07/08/2019
		#BoycottHomeDepot-10/30/2020
		Home Depot-10/07/2022
	Hyatt Hotels Corp	Hyatt-02/27/2021
	Kellogg Co	#DumpKelloggs-11/30/2016
	Kroger Company	#BoycottKroger-08/04/2021

Category	Issuer Name	Trending Topic
	Microsoft Corp	Microsoft-01/22/2021
	New York Times Co	#CancelNYT-08/06/2019
		#CancelNYT-09/26/2019
	Papa John's Intl Inc	Papa John-02/26/2022
		Papa John-03/16/2022
		Papa Johns-11/06/2019
	PayPal Holdings Inc	PayPal-10/08/2022
		PayPal-10/27/2022
	PepsiCo Inc	#BoycottPepsi-01/25/2022
	Sinclair Broadcast Group Inc	Sinclair-04/02/2018
		Sinclair-09/13/2019
	Southwest Airlines Co	Southwest-10/30/2021
	Starbucks Corp	#BoycottStarbucks-01/30/2017
	Stellantis NV	Jeep-02/08/2021
	T J X Companies Inc	TJ Maxx-02/08/2017
	Twitter Inc	#TwitterExposed-05/17/2022
		#TwitterLockOut-02/21/2018
		Twitter-10/14/2020
	Uber Technologies Inc	#BoycottUber-11/11/2019
	Walgreens Boots Alliance Inc	#BoycottWalgreens-02/18/2022
	Walmart Inc	#BoycottWalmart-07/03/2018
		Walmart-12/30/2020
	Wayfair Inc	#WayfairWalkout-06/25/2019
	Whirlpool Corp	Whirlpool-08/06/2020
Gun policy	Amazon Com Inc	#StopNRAmazon-02/22/2018
	Delta Air Lines Inc	Delta-02/24/2018
	Fox Corp	Fox News-05/15/2022
	United Airlines Holdings Inc	United-02/24/2018
	Walmart Inc	#Walmart-09/03/2019
		#BoycottWalmart-08/09/2019
LGBTQ rights	Disney Walt Co	Disney-04/19/2022
		Disney-03/30/2022
	Exxon Mobil Corp	Exxon-04/23/2022
	Fox Corp	#foxnewsj*******toharrystyles-12/30/2020
	Hasbro Inc	Hasbro-02/25/2021
	L Brands Inc	Victoria's Secret-06/16/2021
	Netflix Inc	#NetflixWalkout-10/20/2021
		#cancelonetflix-12/26/2019
	P V H Corp	Calvin Klein-05/12/2022
	Target Corp	Target-11/12/2020
	Yum Brands Inc	Pizza Hut-06/03/2022
Racial equality / policing policy	American Airlines Group Inc	American Airlines-09/07/2020
		American Airlines-10/25/2017
	Bank Of America Corp	Bank of America-09/01/2022
	Delta Air Lines Inc	#BoycottDelta-12/21/2016
	FedEx Corp	#BoycottFedEx-05/20/2020
	Fox Corp	#FoxNewsisRacist-06/06/2020
	General Motors Co	Inside the GM-01/17/2019
	Home Depot Inc	Home Depot-03/23/2022
	Nike Inc	#WalkAwayFromNike-07/02/2019
		Nike-09/03/2018
	Papa John's Intl Inc	Papa John-07/11/2018
		Papa Johns-11/01/2017
	PepsiCo Inc	Pepsi-04/04/2017
	Spotify Technology S A	Spotify CEO-02/07/2022
	Starbucks Corp	#BoycottStarbucks-06/11/2020
		#BoycottStarbucks-07/06/2019
		#BoycottStarbucks-04/14/2018
	Wells Fargo & Co	Wells Fargo-09/22/2020
	Yelp Inc	Yelp-10/09/2020

Appendix B: Variable Definitions

Panel A: Variables Used in Table 4

Variable	Definition	Data Source
Aligned	A binary variable that equals 1 if the poster is ideologically aligned with the prevailing ideological belief of a boycott (i.e., both liberal or both conservative), and equals 0 otherwise.	Twitter Academic API
LikelyBot	A binary variable that equals 1 if one or more of the poster's Botometer bot type scores is higher than 4, and equals 0 otherwise. Note that I exclude the Echo-Chamber bot type in this calculation, because posters tend to have high Echo-Chamber scores when they are highly ideological and frequently repost political posts. The remaining Botometer bot types are: Fake Follower, Financial, Self-Declared, Spammer, and Other.	Botometer API
Opposed	A binary variable that equals 1 if the poster is ideologically opposed to the prevailing ideological belief of a boycott (i.e., one is liberal and the other is conservative), and equals 0 otherwise.	Twitter Academic API
SentTowardsFirm	A categorical variable that can take values -1 (negative), 0 (neutral), or 1 (positive) to indicate a poster's sentiment towards a firm targeted by a trending boycott.	OpenAI ChatGPT analysis of posts downloaded through the Twitter Academic API
PosterVerified	A binary variable that equals 1 if the poster account is verified as of January 2023, and equals 0 otherwise.	Twitter Academic API
AccountAge	The imputed age of a poster's X account (in years) as of their post's release.	Twitter Academic API
FollowerCountRank	Decile ranking of a poster's imputed follower count as of their post's release.	Twitter Academic API
FollowingCountRank	Decile ranking of a poster's imputed following count as of their post's release.	Twitter Academic API
FinCommentExpRank	Decile ranking of cashtag count in post histories spanning five months prior and three months following the post's release.	Twitter Academic API

PostCountRank	Decile ranking of a poster's imputed total post count as of their post's release.	Twitter Academic API

Panel B: Variables Used in Table 5, 6, 7 and 8

Variable	Definition	Data Source
AbRetailTurn[0,+t]	Daily average of retail trading volume over trading days [*0, +t*] divided by total shares outstanding, where *t* takes the values 1, 3, or 7, minus the firm's average retail shares turnover over trading days [−41, −11]. Note that for all abnormal measure calculations, if a firm experienced prior boycotts within the [−41, −11] window, the average (i.e., "normal") measure is instead calculated using the firm's first [−41, −11] window of the calendar year.	TAQ, CRSP
AbROIBVol[0,+t]/ AbROIBTrd[0,+t]	Daily average of retail order imbalance for share volume or number of trades over trading days [*0,+t*] following boycott trending date, where *t* takes the values 1, 3, or 7, minus the mean retail order imbalance for share volume or number of trades over trading days [-41,-11]. Retail buys and sells are classified using the Lee and Ready (1991) algorithm. Retail order imbalance measures are calculated following Boehmer et al. (2021) Eq. (1) and (2).	TAQ
AbTurn[0,+t]	Daily average of trading volume over trading days [*0, +t*] divided by total shares outstanding, where *t* takes the values 1, 3, or 7, minus the firm's average shares turnover over trading days [−41, −11].	CRSP
AbVola[0,+t]	Standard deviation of raw stock returns over trading days [*0,+t*] window following boycott trending date, where *t* takes the values 3 or 7, minus the standard deviation of raw stock returns over trading days [-41,-11] .	CRSP
AbIVola[0,+t]	Daily average of intraday return volatility over trading days [*0,+t*] following boycott trending date, where *t* takes the values 1, 3, or 7, minus the mean intraday return volatility over trading days [-41,-11].	TAQ
AvgSentTowardsFirm	Average sentiment of posts referencing the boycotted firm's cashtag, measured at the boycott level on day 0 and day +1. Note that technical analysis posts are included when calculating this variable (ads and spams are still excluded.)	OpenAI ChatGPT analysis of posts downloaded through the Twitter Academic API
AvgTradMediaSent	Average sentiment of all news articles mentioning the boycotted firm on day 0 and day +1. It ranges from -1 to 1, with -1 (1) indicating the most negative (positive) sentiment.	RavenPack Analytics 1.0
BHAR[0,+t]	Market-adjusted buy-and-hold abnormal returns over trading days [*0,+t*] following boycott trending date, where *t* takes the values 1, 3, or 7.	CRSP
BTM	The boycotted firm's book value of equity to market value of equity ratio as of the most recent fiscal quarter end.	CRSP and Compustat

BoycotterIdeology	A binary variable that indicates the prevailing ideology of a boycott. 0 indicates that the boycott is consistent with liberal ideological beliefs, whereas 1 indicates that the boycott is consistent with conservative ideological beliefs.	Twitter Academic API
IdeoDiversityScore	One over the sum of the squares of the percentages of three types of posters: aligned, opposed, and nonpartisan.	Twitter Academic API
LogCashtagCount	Log of one plus the total number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
LogNumAnalysts	Log of one plus the number of analysts who issued forecasts for the boycotted firm over the most recent fiscal quarter.	I/B/E/S
LogSize	Log of one plus the boycotted firm's market value of equity as of the most recent fiscal quarter end.	CRSP
LogTradMediaCount	Log of one plus the total number of news articles mentioning the boycotted firm on day 0 and day +1.	RavenPack Analytics 1.0
PctInstOwn	Number of shares owned by institutional investors as a percentage of the target firm's total number of shares outstanding as of the most recent month end.	WRDS SEC Analytics Suite
PctPosterAligned	Number of posts by posters ideologically aligned with the boycotters, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_Pos(Zero)Imp	Number of posts by posters ideologically aligned with the boycotters that have at least one like, reply, or retweet (no likes, replies, or retweets), divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_(No)Link	Number of posts by posters ideologically aligned with the boycotters that (do not) include hyperlinks, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_(Not)Repost	Number of posts by posters ideologically aligned with the boycotters that are (not) reposts, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_Fin (Ideo)Only	Number of posts by posters ideologically aligned with the boycotters that only reference financial performance (ideological beliefs), divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_Both(Neither)	Number of posts by posters ideologically aligned with the boycotters that are reference both (neither) financial performance and (nor) ideological beliefs, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
PctPosterAligned_Hi(Lo)Inf	Number of posts by posters who are ideologically aligned with the boycotters and have above (below) median follower counts, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API

PctPosterAligned_Hi (Lo)Exp	Number of posts by posters who are ideologically aligned with the boycotters and have above (below) median eight-month cashtag counts, divided by number of posts referencing the boycotted firm's cashtag on day 0 and day +1.	Twitter Academic API
ROA	The boycotted firm's net income divided by its total assets as of the most recent fiscal quarter end.	Compustat
StdTradMediaSent	Standard deviations of sentiment of all news articles mentioning the boycotted firm on day 0 and day +1.	RavenPack Analytics 1.0

Notes: This table provides detailed definitions for variables used in regression analyses.

Appendix C: ChatGPT Prompts for Textual Classifications

Panel A: Classification of Post Sentiment Towards Boycotted Firms

Please answer the following question about the post: What is the sentiment expressed towards {cashtag} in the post? [Positive/Neutral/Negative]

Important instructions:

-Think step by step.

-Explain your answer in a lot of detail, but no more than 5 sentences.

-If the answer is unclear, answer Neutral. The final answer can only be Positive or Neutral or Negative.

-If the returned JSON object contains double quotation marks, make sure to use backslashes to escape them properly.

-Provide answers in the following JSON format:

{{

"explanation”: <explanation>,

"final_answer”: <Positive/Neutral/Negative>

}}

The post in question:

{clean_text}

Answer:

Panel B: Classification of Post Focus (Financial Value vs. Ideological Identity)

Please answer the following two questions about the post:

1. Does the post contain language specifically related to the past, current, or future economic, financial, or stock market performance of {cashtag}? [Yes/No]

- Important instructions:

A. Simply mentioning a company's ticker/cashtag or mentioning trading stocks does NOT count as economic/financial language on its own.

B. Any mention or implication that an event, action, or circumstance could positively or negatively affect the company's performance—including stock price, sales, profits, brand reputation, customer loyalty, future growth, or other outcomes—should be considered "Yes."

C. If there is no clear or implied directional impact on the company's performance, answer "No."

2. Does the post contain language that expresses political or ideological opinions? [Yes/No]

- Important instructions:

A. Simply mentioning political events, political figures, or a boycott does NOT count as political or ideological opinion on its own.

B. Political or ideological opinions must express the author's views or feelings about political identity, ideology, social or cultural issues, or partisan statements.

Additional Important instructions:

- Consider each aspect carefully.

- Explain your answer with detail, but limit to 5 sentences.

- If the returned JSON object contains double quotation marks, make sure to use backslashes to escape them properly.

- Provide answers exactly in the following JSON format and do not include any text outside this JSON:

[

{{\"id\" : 1, \"explanation\" : <explanation_why_answer_1>, \"answer\" : <answer_1>}},

{{\"id\" : 2, \"explanation\" : <explanation_why_answer_2>, \"answer\" : <answer_2>}}

]

The post in question:

{clean_text}

Answer:

Appendix D: Example ChatGPT (GPT-4) Classifications of Post Sentiment Towards Boycotted firms

Panel A: Trending topic – #BoycottCVS (8/15/2019)

Positive towards $CVS:
Not sure what all the hub bub is about nor do I care. Must be a bunch of anti vaxxers with flu shots seeing its school time again... All y'all doing is bringing attetention [sic] to $CVS. Thanks for the bump in my stocks!#BoycottCVS. Retrieved from https://x.com/Coleman4Nh/status/1162050965517873154
$CVS pulling above resistance with nice volume Crypto dumping in continued months chop following 18 months of 90% losses and almost all alts and 80% loss on Bitcoin. <link> Retrieved from https://x.com/CryptoLain/status/1162058845126057984
Neutral towards $CVS:
Jefferies Financial Group Comments on CVS Health Corp's Q3 2019 Earnings $CVS <link> #stocks Retrieved from https://x.com/AmericanBanking/status/1161956528917753856
$CVS - Current Report Filing (8-k) <link> Retrieved from https://x.com/JUIVEDUMAROC/status/1162097156238520321
Negative towards $CVS:
$CVS #CVSDeniesCare #BoycottCVS is trending and accelerating on X due to denial of coverage for BC pills thru mail order startup NuRx and The Pill Club. Denial likely due to cos apply for coverage as retailer, but really mail order. About to blow up BIG TIME. BEARISH!!! <link> Retrieved from https://x.com/larrywabrams/status/1162079384469045248
@AngelaBelcamino This is the same board of directors that has driven #CVS into the ground. Won't be too much longer before $AMZN and $WMT put $CVS out of its misery 🤑. Retrieved from https://x.com/realudaypalled/status/1162081968613445633

Panel B: Trending topic – Nike (9/3/2018)

Positive towards $NKE:
@ClayTravis @DanishaDanielle @Nike Aren't you a free-market capitalist conservative? You can't have it both ways. If the market dictates that Colin Kaepernick is worth that much--more power to him. I know I'll be adding to my $NKE position and buying more #Nike shoes and apparel because of this. Stay mad Clay. Retrieved from https://x.com/AbeFroman/status/1036744818871820288
@myhedghog @Nike Polarizing brands, brands with a POV stand out and thrive. Middle of the road consensual brands never do. It's a smart move. $NKE. Retrieved from https://x.com/jfhksar88/status/1036750123609538562
Neutral towards $NKE:
Colin Kaepernick, who is suing NFL owners for allegedly colluding to keep him out of the league, is one of the faces of a new Nike campaign to commemorate the 30th anniversary of the brand's iconic "Just Do It" motto. $NKE <link> Retrieved from https://x.com/SteveKopack/status/1036710414913036289
Wooooo buddy cue all the $NKE posts. Retrieved from https://x.com/tycolby/status/1036701591712219137

Negative towards $NKE:
@darrenrovell This will go well tomorrow when $NKE opens up for trading. My bet is this ad will be pulled by Wednesday. Public companies should NEVER get political, never. Retrieved from https://x.com/highyield6/status/1036707275065442304
Time to short $NKE? #JustDoIt <link> Retrieved from https://x.com/juniorminingpro/status/1036729429605548032

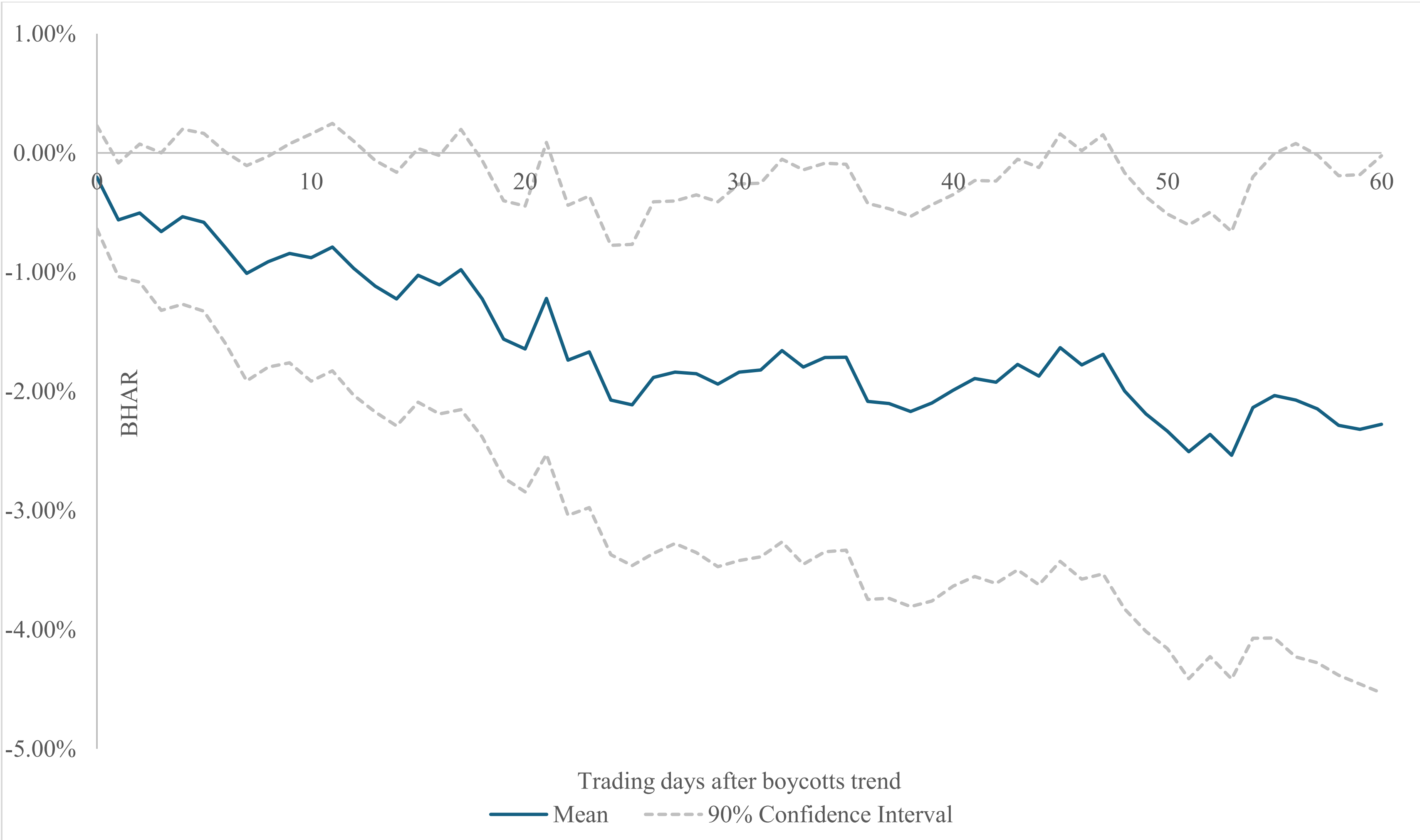
Notes: This table displays posts made when "#BoycottCVS" and "Nike" trended on X and their sentiment towards the boycotted firms (CVS and Nike) as detected by GPT-4. "#BoycottCVS" trended on Aug 15, 2019, when liberal posters criticized CVS Caremark pharmacy for allegedly lowering reimbursement rates for contraceptives (https://www.usatoday.com/story/money/2019/08/15/cvs-boycott-pill-club-calls-out-drug-stores-birth-control-rates/2022966001/). "Nike" trended on Sept 3, 2018, when conservative X posters blasted the firm's controversial ad campaign featuring Colin Kaepernick (https://www.nytimes.com/2018/09/03/sports/kaepernick-nike.html). Hyperlinks in the posts are represented as <link> for brevity.

Appendix E: Example ChatGPT (GPT-4o) Classifications of Financial Value vs. Identity Congruence-Focused Posts (Trending Topic – #DumpKelloggs)

Posts focusing on financial value:
insider selling, chart hella bearish, & Uber/$AMZN soon to be competition? I see $10 PPS, then BK in your future $GRUB Retrieved from https://x.com/TheWeedSeeker/status/797053003719131136
I understand emotions but this is bad for business - half the country (and probably the company) has a different opinion $GRUB #ShortSale Retrieved from https://x.com/HarschCapital/status/797061778710601728
Posts focusing on identity congruence:
@M3aloney YOU ARE A RACIST! YOU ARE GARBAGE! SHORT AND SELL $GRUB Retrieved from https://x.com/CoolVideoBro/status/797076026757173248
Selling all of my $grub shares!! That CEO is very intolerant. What a joke! Retrieved from https://x.com/bighoots4/status/797076449001881600
Posts focusing on financial value *and* identity congruence:
The "tolerant" left like @M3aloney & his company $GRUB stock is down 6% today! There is joy in mudville! #BoycottGubHub Retrieved from https://x.com/15minofPham/status/797128829391294464
Looking forward to shorting this POS. $GRUB Trades @ 10 x revs w p/e of 70. NOT a Trump economy stock #boycottgrub <link> Retrieved from https://x.com/KHerriage/status/796909808637145089
Posts focusing on *neither* financial value *nor* identity congruence:
$GRUB covered 34.75 Retrieved from https://x.com/mjsoldit_/status/797129425582194689
$GRUB Stock Option Volume Spikes 1.9x its Average <link> <link> Retrieved from https://x.com/MarketChmln/status/797182491350171648

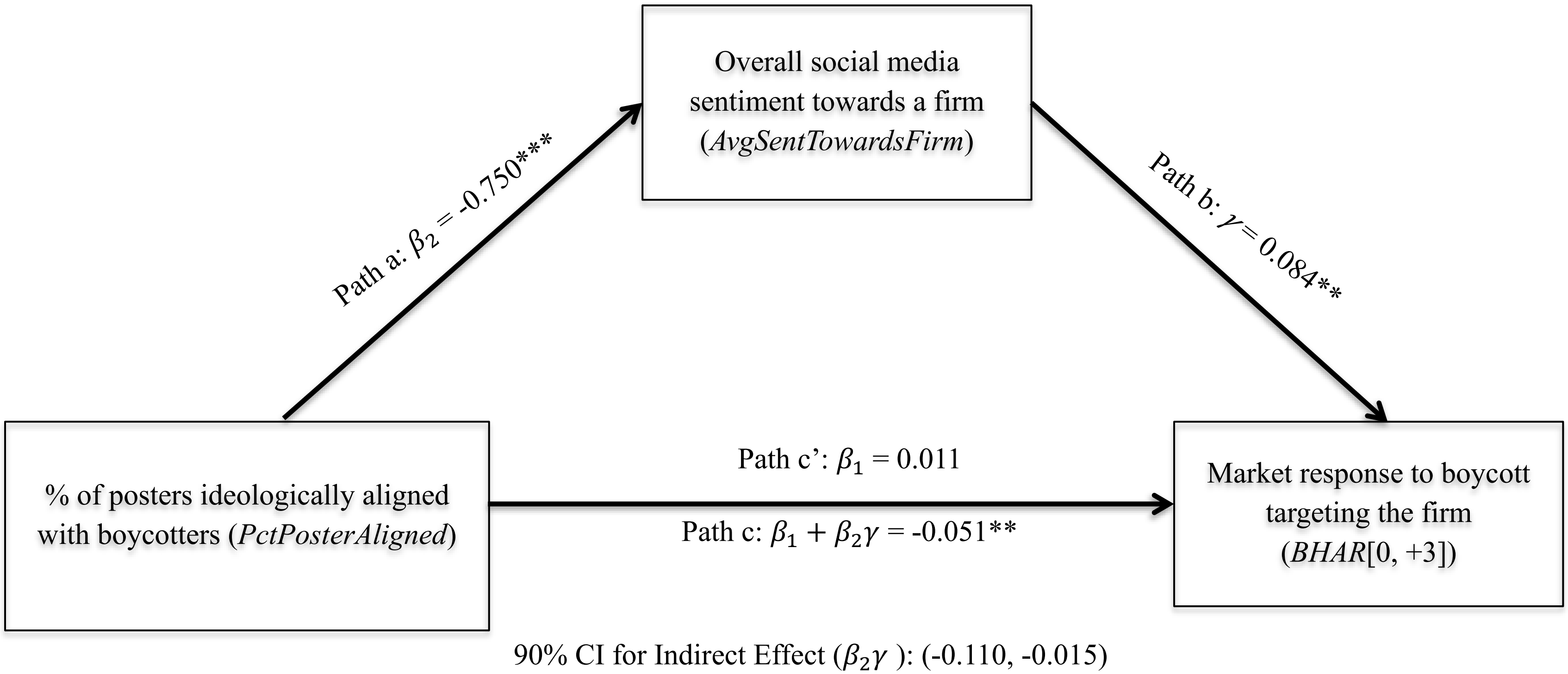
Notes: This table displays posts created when "Grubhub CEO" trended on X and their focuses as detected by GPT-4o. "Grubhub CEO " trended on Nov 11, 2016, when conservatives attacked Grubhub's CEO for sending an anti-Trump email to employees (https://time.com/4567760/grubhub-ceo-trump-email/). Hyperlinks in the posts are represented as <link> for brevity.

Figure 1: Post-Boycott *BHAR* and 90% Confidence Interval



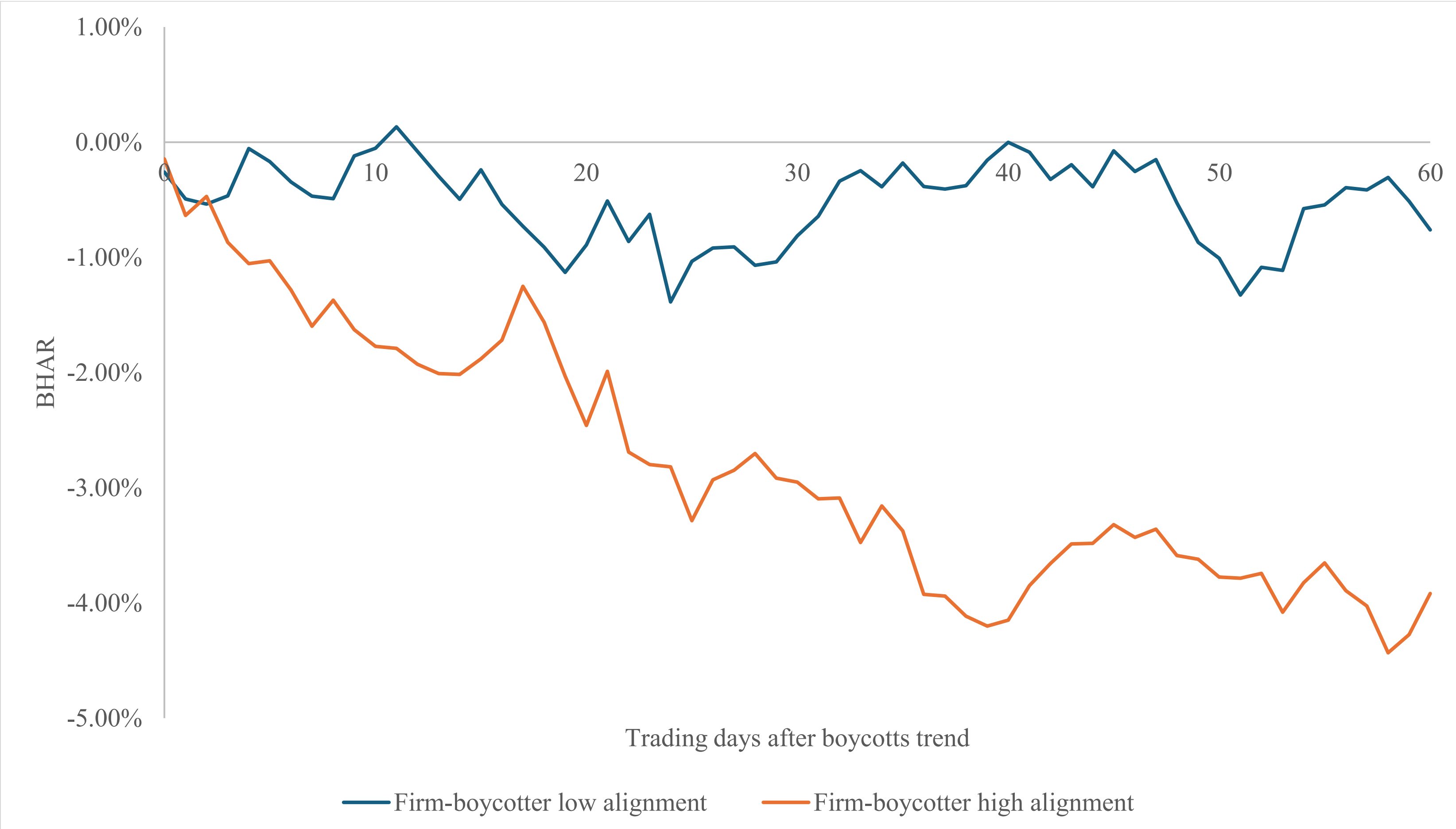
Notes: This figure shows the mean and 90% confidence interval of market-adjusted buy-and-hold abnormal returns over the [-1, +60] trading day window around boycott trending dates.

Figure 2: Path Analysis Diagram – Hypothesis 1 Mediation Analysis



Notes: This figure graphically displays the mediation model used to substantiate Hypothesis 1. For visual simplicity, I only display coefficients estimated with *BHAR*[0,+3] as the dependent variable. Path a represents the effect of *PctPosterAligned* on *AvgSentTowardsFirm*. Path b represents the effect of *AvgSentTowardsFirm* on *BHAR*[0, +3]. Path c' represents the direct effect of *PctPosterAligned* on *BHAR*[0, +3]. Path c represents the total effect (indirect effect plus direct effect). The t-statistic and one-sided 90% confidence interval for the indirect effect is calculated based on bootstrapped standard errors with 5,000 replications. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, in a one-tailed test when a directional prediction is specified and a two-tailed test otherwise.

Figure 3: Post-Boycott *BHAR* by Firm-Boycotter Alignment



Notes: This figure shows, by ideological alignment of firms and boycotters, the mean of market-adjusted buy-and-hold abnormal returns over the [-1, +60] trading day window around boycott trending dates. Firms are classified as ideologically aligned (misaligned) with boycotters if at least (less than) 50% of their employees share the prevailing ideology of the boycott (i.e., both liberal or conservative).

Table 1: Sample Construction

Panel A: Firm-Level Sample Selection

	Number of boycotts	Number of unique firms
Trending boycotts targeting publicly traded companies from April 2016 through October 2022	256	92
Exclude: boycotts resulting from non-ideologically polarizing issues or whose boycotter ideology is ambiguous	(125)	(29)
Exclude: firms whose cashtags were never discussed on X	(1)	(1)
Exclude: foreign ADRs	(5)	(4)
Initial sample	125	58

Panel B: Post-Level Sample Selection

	Number of posts	Number of unique posters
Initial sample	135,943	59,934
Exclude: posts made outside the [0, +1] day window	(39,731)	(13,889)
Exclude: posts that are pure technical analyses	(9,936)	(2,924)
Exclude: posts that are pure advertisements or spams	(8,699)	(2,429)
Exclude: posts missing control variables	(387)	(252)
Final sample	77,190	40,440

Notes: This table describes the sample selection procedure. Boycotts in the following categories are not ideologically polarizing according to the USC Polarization Index and therefore excluded: Business Events, Corporate Misconduct, Employee Rights, Gender Equality/Sexual Misconduct, Popular Culture Controversy, Privacy Breaches/Data Leaks, Product Safety/Customer Complaints, and Unfounded Rumors.

Table 2: Descriptive Statistics of Posters and Ideologically Polarizing Boycotts

Panel A: Most Common Unique Words in Poster Profiles by Political Ideology

Ideology	Most Common Unique Words in Poster Profile
Liberal (N=19,167)	voteblue (138), bidenharris (76), bluewave (45), standwithukraine (43), gqp (26), strongertogether (24), justicematters (23), goodtrouble (23), stillwithher (21), khive (19), votebluenomatterwho (18), indivisible (18), getvaccinated (16), stopasianhate (15), voters (15)
Conservative (N=23,721)	pureblood (75), ultramaga (74), gab (43), trudeaumustgo (27), desantis (26), lgbfjb (23), lgb (21), draintheswamp (20), bluelivesmatter (19), populist (17), endthefed (16), comply (14), ccot (14), unvaxxed (13), saveamerica (13)
Nonpartisan (N=10,829)	owler (9), alertchart (8), tranding (8), trialists (7), enrgygreen (7), enrgy (7), mathfabot (6), mathcvb (6), mymetatrader (6), mathcabot (6), mathatb (6), whitelist (6), mathctbot (6), mathcobot (5), mathapb (5)

Panel B: Number of Boycotts by Issue Category and Boycotter Ideology

Category	Number of liberal boycotts	Number of conservative boycotts	Total
Abortion	3	1	4
COVID-19	11	9	20
Climate change	2	0	2
Domestic / international politics	46	17	63
Gun policy	3	3	6
LGBTQ rights	3	8	11
Racial equality / policing policy	12	7	19
Total	**80**	**45**	**125**

Panel C: Summary Statistics on Events That Triggered Boycotts

Category	Sub-category	Number of Boycotts
Firm action (n=82)	Firm's product/operational decision	47
	Firm's human resource decision/policy	15
	Firm's political contribution/advocacy	11
	Firm's marketing/PR decision	8
	Firm's disclosure	1
Employee action (n=26)	Current executive statement/action	12
	Current employee statement/action	9
	Former executive statement/action	4
	Former employee statement/action	1
Other (n=17)	Non-firm action	8
	Firm inaction	4
	Subsidiary/franchisee action	5
Total		**125**

Table 2 (continued)

Panel D: Number of Posts and Average Poster Sentiment

	Liberal boycotts		Conservative boycotts		All boycotts	
Issue category	**Avg. # of posts**	**Avg. post sentiment**	**Avg. # of posts**	**Avg. post sentiment**	**Avg. # of posts**	**Avg. post sentiment**
Abortion	595	0.09	44	0.02	458	0.09
COVID-19	231	0.02	687	-0.05	436	-0.03
Climate change	305	-0.18	-	-	305	-0.18
Domestic / international politics	366	-0.13	1,616	-0.23	703	-0.19
Gun policy	651	0.01	169	0.12	410	0.03
LGBTQ rights	1,365	0.09	619	-0.13	823	-0.03
Racial equality / policing policy	419	-0.24	740	-0.13	538	-0.19
Total	411	-0.09	985	-0.18	618	-0.14

Panel E: Means and Medians of Poster Characteristics by Political Ideology

	Liberals (N = 13,935)	**Conservatives (N = 18,513)**	**Nonpartisans (N = 7,992)**
CountLiberalFollowing	54.61	5.45	0.40
	(17)	*(1)*	*(0)*
CountConservativeFollowing	6.19	66.23	0.40
	(2)	*(24)*	*(0)*
SentTowardsFirm	-0.15	-0.28	-0.03
	(0)	*(0)*	*(0)*
PosterVerified	0.04	0.01	0.01
	(0)	*(0)*	*(0)*
AccountAge	6.87	5.60	4.03
	(7.40)	*(5.11)*	*(2.41)*
FollowerCount	10,671.89	3,857.91	4,640.33
	(681)	*(430)*	*(185)*
FollowingCount	2,430.73	1,807.33	493.72
	(1,060)	*(702)*	*(120)*
PostCount	72,871.16	43716.45	29,375.53
	(19,857)	*(13,207)*	*(4,864)*
FinCommentExp	484.70	454.94	2,684.34
	(11)	*(16)*	*(157)*
LikelyBot	0.02	0.02	0.18
	(0)	*(0)*	*(0)*

Notes: This table displays descriptive statistics of ideologically polarizing social media boycotts. Panel A shows the most common words used in poster profiles for each ideology group that are not used by other groups (word frequencies are in parentheses; stop words and non-English words are excluded). Panel B shows the number of boycotts in each category. Panel C shows descriptive statistics on the type of events triggering boycotts. Panel D shows, by category and boycotter ideology, the average number of posts made when the boycotts trended on X and the day after, as well as average post sentiment. Panel E shows, by poster ideology, mean and median poster characteristics, with medians italicized and in parentheses.

Table 3: Descriptive Statistics of Regression Variables

Panel A: Post Level Summary Statistics for Regression Variables Used in Table 4

	N	Mean	SD	p25	p50	p75
SentTowardsFirm	77,190	-0.14	0.55	0.00	0.00	0.00
Aligned	77,190	0.42	0.49	0.00	0.00	1.00
Opposed	77,190	0.30	0.46	0.00	0.00	1.00
PosterVerified	77,190	0.03	0.18	0.00	0.00	0.00
AccountAge	77,190	5.54	4.27	1.38	4.96	9.33
FollowerCount	77,190	16,417.45	356,500.60	95.39	505.91	2,351.15
FollowingCount	77,190	1,444.98	7,091.44	58.75	326.99	1,214.05
PostCount	77,190	93,218.04	277,148.90	3,122.13	13,619.39	56,249.42
FinCommentExp	77,190	17,847.07	65,336.35	13.00	268.50	2,433.00
LikelyBot	77,190	0.15	0.36	0.00	0.00	0.00

Panel B: Boycott Level Summary Statistics for Regression Variables Used in Tables 5, 6, 7, and 8

Stats	N	Mean	SD	p25	p50	p75
BHAR(0, +3)	125	-0.59%	4.33%	-2.54%	-0.06%	1.98%
AbTurn(0,+3)	125	0.16%	0.94%	-0.19%	-0.04%	0.25%
AbVola(0,+3)	125	0.05%	1.54%	-0.79%	-0.18%	0.64%
AbIVola(0,+3)	125	2.27%	16.62%	-1.80%	-0.34%	2.63%
AbROIBVol(0,+3)	125	-0.65%	7.78%	-5.82%	0.05%	4.73%
AbROIBTrd(0,+3)	125	-0.29%	8.85%	-4.76%	-0.44%	4.66%
AbRetailTurn(0,+3)	125	0.00%	0.11%	-0.01%	0.00%	0.01%
PctPosterAligned	125	35.13%	15.05%	24.49%	33.96%	42.00%
IdeoDiversityScore	125	2.59	0.44	2.41	2.76	2.89
AvgSentTowardsFirm	125	-0.10	0.22	-0.19	-0.03	0.05
BoycotterIdeology	125	0.36	0.48	0.00	0.00	1.00
LogCashtagCount	125	5.44	1.56	4.39	5.66	6.58
LogSize	125	24.58	1.78	23.38	24.42	26.19
BTM	125	0.46	0.73	0.08	0.23	0.53
ROA	125	0.02	0.02	0.00	0.01	0.03
PctInstOwn	125	0.74	0.19	0.64	0.74	0.88
LogNumAnalysts	125	3.14	0.47	2.94	3.18	3.43
AvgTradMediaSent	125	0.00	0.07	-0.01	0.00	0.02
StdTradMediaSent	125	0.06	0.07	0.00	0.05	0.08
LogTradMediaCount	125	2.04	1.38	1.10	2.20	2.89

Notes: This table presents descriptive statistics of regression variables. Panel A presents the summary statistics of variables used in Table 4. *FollowerCount, FollowingCount, PostCount,* and *FinCommentExp* are displayed in raw numbers instead of decile rankings. Panel B presents the summary statistics of variables used in Tables 5, 6, 7, and 8. All continuous variables, except for stock returns, are winsorized at the 1st and 99th percentiles.

Table 4: Test of the Relation Between Poster-Boycotter Ideological Alignment and Poster Sentiment Towards Boycotted firms

Panel A: Poster-Boycotter Ideological Alignment and Sentiment Towards Boycotted Firms

VARIABLES	**Pred. Sign**	(1) Full Sample	(2) Posts with ≤5 cashtags only	(3) Posts with ≤5 cashtags & posters with above-median financial commentary experience only	(4) Posts with ≤5 cashtags & posters who self-describe as traders only
Aligned	(-)	-0.096***	-0.108***	-0.081***	-0.109***
		(-3.242)	(-2.760)	(-3.139)	(-3.858)
Opposed	(+)	-0.008	-0.014	0.002	-0.012
		(-0.326)	(-0.439)	(0.075)	(-0.486)
PosterVerified	(?)	0.019	0.025	0.050*	0.027
		(1.019)	(1.307)	(1.884)	(0.718)
AccountAge	(?)	0.003	0.002	0.003	0.005**
		(1.279)	(0.981)	(1.461)	(2.577)
FollowerCountRank	(?)	0.006**	0.006*	0.003	0.004
		(2.424)	(1.820)	(0.671)	(0.925)
FollowingCountRank	(?)	-0.002	-0.002	-0.002	0.002
		(-1.174)	(-1.006)	(-0.521)	(0.550)
PosterPostCountRank	(?)	-0.015**	-0.014*	-0.015***	-0.023***
		(-2.525)	(-1.914)	(-3.043)	(-4.228)
FinCommentExpRank	(?)	0.016*	0.013	0.028***	0.023***
		(1.709)	(1.197)	(4.381)	(4.496)
LikelyBot	(?)	0.060***	0.076***	0.039**	0.063***
		(3.796)	(3.195)	(2.135)	(2.682)
Boycott FE		YES	YES	YES	YES
Clustering		By firm and by poster	By firm and by poster	By firm and by poster	By firm and by poster
Observations		77,190	62,003	27,403	17,098
Adj. R-squared		0.172	0.180	0.113	0.124

Table 4 (continued)

Panel B: Poster-Boycotter Ideological Alignment and Poster Sentiment Towards Boycotted Firms (Excluding Posters with High Bot Scores)

VARIABLES	**Pred. Sign**	(1) Full Sample	(2) Posts with ≤5 cashtags only	(3) Posts with ≤5 cashtags & posters with above-median financial commentary experience only	(4) Posts with ≤5 cashtags & posters who self-describe as traders only
Aligned	(-)	-0.109***	-0.123**	-0.109***	-0.131***
		(-3.013)	(-2.534)	(-2.888)	(-3.285)
Opposed	(+)	-0.015	-0.023	-0.010	-0.018
		(-0.554)	(-0.686)	(-0.359)	(-0.579)
Controls		YES	YES	YES	YES
Boycott FE		YES	YES	YES	YES
Clustering		By firm and by poster	By firm and by poster	By firm and by poster	By firm and by poster
Observations		65,262	53,171	19,328	11,730
Adj. R-squared		0.180	0.184	0.118	0.132

Notes: This table presents the results of regression analyses at the post level. Panel A presents the regression results of the relationship between poster-boycotter ideological alignment and post sentiment. Panel B repeats the test in Panel A except that posts by posters with high bot scores are excluded. Decile rankings of *FollowerCount, FollowingCount, PostCount,* and *FinCommentExp* are used to accommodate data non-normality and outliers. Continuous variables are winsorized at the 1st and 99th percentiles. See Appendix B for detailed variable definitions. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, in one-tailed tests if a directional prediction is specified and two-tailed tests otherwise.

Table 5: Descriptive Analyses of Market Reaction to Boycotts

Panel A: Mean and Median *BHAR* in Windows Surrounding Boycotts

	Mean	Median
BHAR(-15, -11)	-0.27%	0.04%
BHAR(-10, -6)	-0.41%	-0.54%
BHAR(-5, -1)	0.46%	0.22%
BHAR(0, +1)	-0.51%*	-0.34%**
BHAR(0, +3)	-0.59%	-0.07%
BHAR(0, +7)	-0.95%*	-0.54%

Panel B: Cross-Sectional Variation in *BHAR* by Poster-Boycotter Ideological Alignment

	Poster-boycotter high alignment (n=17)	Poster-boycotter low alignment (n=108)	Diff (high - low)
BHAR(0, +1)	-1.21%*	-0.40%	-0.81%
BHAR(0, +3)	-1.56%*	-0.44%	-1.12%
BHAR(0, +7)	-1.06%	-0.93%	-0.13%

Notes: This table presents *BHAR*s over various windows around the 125 boycotts. Panel A presents mean and median *BHAR*s over windows surrounding the boycotts. Panel B presents mean post-boycott *BHAR*s by poster-boycotter ideological alignment. High (low) alignment is defined as cases where at least (less than) 50% of posters are ideologically aligned with boycotters. For mean (median) *BHAR*s, *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels in a two-tailed t-test (signed rank test), respectively.

Table 6: Ideology-Driven Social Media Opinions and Market Reaction to Boycotts

Panel A: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts

VARIABLES	Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned	(-)	-0.026*	-0.051**	-0.057**
		(-1.58)	(-2.29)	(-1.87)
BoycotterIdeology	(?)	-0.003	0.001	0.016
		(-0.50)	(0.15)	(1.10)
LogCashtagCount	(?)	-0.004*	-0.000	-0.002
		(-1.99)	(-0.08)	(-0.44)
LogSize	(?)	-0.000	0.001	0.006
		(-0.11)	(0.26)	(0.77)
BTM	(?)	0.000	0.007	0.006
		(0.06)	(1.10)	(0.60)
ROA	(?)	0.092	-0.012	-0.021
		(1.03)	(-0.07)	(-0.09)
PctInstOwn	(?)	-0.003	-0.002	-0.012
		(-0.19)	(-0.10)	(-0.31)
LogNumAnalyst	(?)	0.008	0.010	0.016
		(0.54)	(0.46)	(0.61)
AvgTradMediaSent	(+)	0.082**	0.118**	0.185***
		(1.92)	(2.16)	(2.52)
StdTradMediaSent	(?)	-0.004	-0.069	-0.188
		(-0.06)	(-0.81)	(-1.53)
LogTradMediaCount	(?)	0.004	-0.002	-0.003
		(1.33)	(-0.40)	(-0.61)
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.064	0.015	0.028

Table 6 (continued)

Panel B: Path Analysis Using Average Social Media Sentiment Towards the Boycotted Firm as the Mediating Variable

		Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
Total Effect		(-)	-0.026*	-0.051**	-0.057**
			(-1.58)	(-2.29)	(-1.87)
Direct Effect		(?)	0.006	0.011	-0.006
			(0.17)	(0.24)	(-0.12)
Indirect Effect		(-)	-0.032	-0.063**	-0.051
			(-1.20)	(-1.70)	(-1.25)
% Effect					
	Direct		-23%	-22%	11%
	Indirect		123%	122%	89%
Controls			YES	YES	YES
Day of week FE			YES	YES	YES
Year FE			YES	YES	YES
Observations			125	125	125
Adj. R-squared			0.064	0.015	0.028

Notes: This table presents the regression results of testing Hypothesis 1. Panel A presents the main regression, and Panel B presents the results of the path analysis. Note that in Panel B, t-statistics of the total and direct effects are calculated based on standard errors clustered by firm, whereas t-statistics of the indirect effect is calculated based on bootstrapped standard errors with 5,000 replications. See Appendix B for detailed variable definitions. Continuous variables are winsorized at the 1st and 99th percentiles. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, in a one-tailed test if a directional prediction is specified, and two-tail test otherwise.

Table 7 Cross-Sectional Variation in The Relation Between Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts

Panel A: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Post Impression

VARIABLES	**Pred. Sign**	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_PosImp	(-)	-0.038***	-0.055***	-0.059**
		(-4.25)	(-3.75)	(-2.26)
PctPosterAligned_ZeroImp	(-)	0.012	0.072	-0.031
		(0.34)	(1.26)	(-0.38)
Difference	**(?)**	**-0.050**	**-0.127****	**-0.028**
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.111	0.059	0.043

Panel B: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Existence of Hyperlinks

VARIABLES	**Pred. Sign**	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_NoLink	(-)	-0.062***	-0.106***	-0.120***
		(-4.81)	(-4.28)	(-3.15)
PctPosterAligned_Link	(-)	-0.007	0.012	-0.013
		(-0.50)	(0.45)	(-0.42)
Difference	**(?)**	**-0.055****	**-0.118****	**-0.107***
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.135	0.079	0.083

Table 7 (Continued)

Panel C: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Repost Status

VARIABLES	Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_Repost	(-)	-0.036***	-0.049***	-0.063***
		(-3.59)	(-3.41)	(-2.56)
PctPosterAligned_NotRepost	(-)	-0.004	0.022	-0.016
		(-0.10)	(0.39)	(-0.22)
Difference	**(?)**	**-0.032**	**-0.071**	**-0.047**
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.103	0.027	0.047

Panel D: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Post Focus

VARIABLES	Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_FinOnly	(-)	-0.025**	-0.060***	-0.116***
		(-1.81)	(-2.74)	(-3.17)
PctPosterAligned_IdeoOnly	(-)	-0.014	-0.070	-0.072
		(-0.30)	(-0.83)	(-1.05)
PctPosterAligned_Both	(-)	-0.045**	-0.085***	-0.015
		(-2.28)	(-2.43)	(-0.28)
PctPosterAligned_Neither	(-)	-0.038**	0.024	0.012
		(-2.21)	(0.68)	(0.24)
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.089	0.040	0.064

Table 7 (Continued)

Panel E: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Poster Influence

VARIABLES	Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_HiInf	(-)	-0.092***	-0.083	-0.189**
		(-2.69)	(-1.13)	(-2.06)
PctPosterAligned_LoInf	(-)	-0.001	-0.015	0.007
		(-0.07)	(-0.37)	(0.16)
Difference	**(?)**	**-0.091***	**-0.068**	**-0.196**
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.122	0.021	0.073

Panel F: Ideology-Driven Social Media Opinions and *BHAR* Following Boycotts – By Poster Experience with Financial Commentary

VARIABLES	Pred. Sign	(1) *BHAR(0,+1)*	(2) *BHAR(0,+3)*	(3) *BHAR(0,+7)*
PctPosterAligned_HiExp	(-)	-0.037***	-0.053***	-0.071***
		(-3.14)	(-2.99)	(-2.60)
PctPosterAligned_LoExp	(-)	-0.015	0.001	-0.020
		(-0.71)	(0.01)	(-0.43)
Difference	**(?)**	**-0.022**	**-0.054**	**-0.051**
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adj. R-squared		0.104	0.028	0.053

Notes: This table presents regression results examining how various variables moderate the relationship between ideology-driven social media opinions and market reaction to boycotts. Panels A-F present regression results using different partitioning variables: post engagement (A), presence of hyperlinks (B), repost status (C), post focus (D), poster influence (E), and poster experience with financial commentary (F). See Appendix B for detailed variable definitions. Continuous variables are winsorized at the 1st and 99th percentiles. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, in a one-tailed test if a directional prediction is specified, and two-tailed test otherwise.

Table 8: Ideological Diversity and Investor Disagreement Following Polarizing Boycotts

Panel A: Ideological Diversity and Abnormal Turnover Following Polarizing Boycotts

VARIABLES	**Pred.**	(1) *AbTurn(0,+1)*	(2) *AbTurn(0,+3)*	(3) *AbTurn(0,+7)*
IdeoDiversityScore	(+)	0.005***	0.004***	0.004***
		(2.94)	(2.67)	(2.44)
BoycotterIdeology	(?)	-0.006**	-0.005**	-0.005**
		(-2.05)	(-2.36)	(-2.56)
LogCashtagCount	(+)	0.004***	0.002***	0.001*
		(3.58)	(2.62)	(1.44)
LogSize	(?)	-0.005**	-0.002*	-0.002
		(-2.63)	(-1.90)	(-1.14)
BTM	(?)	-0.004*	-0.002	-0.001
		(-1.76)	(-1.07)	(-0.83)
ROA	(?)	0.060	0.030	0.025
		(0.95)	(0.60)	(0.51)
PctInstOwn	(?)	-0.006	-0.001	-0.001
		(-0.67)	(-0.21)	(-0.19)
LogNumAnalysts	(?)	-0.009**	-0.007**	-0.004
		(-2.12)	(-2.13)	(-1.40)
AvgTradMediaSent	(?)	-0.039**	-0.029**	-0.026**
		(-2.22)	(-2.24)	(-2.22)
StdTradMediaSent	(+)	0.035**	0.023*	0.019*
		(1.82)	(1.46)	(1.35)
LogTradMediaCount	(+)	0.002**	0.002***	0.001**
		(2.18)	(2.45)	(1.73)
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adjusted R-squared		0.467	0.327	0.176

Table 8 (Continued)

Panel B: Ideological Diversity and Abnormal Daily Return Volatility Following Polarizing Boycotts

VARIABLES	**Pred. Sign**	(1) *AbVola(0,+3)*	(2) *AbVola(0,+7)*
IdeoDiversityScore	(+)	0.006**	0.007**
		(2.00)	(2.11)
Controls		YES	YES
Day of week FE		YES	YES
Year FE		YES	YES
Clustering		By firm	By firm
Observations		125	125
Adjusted R-squared		0.091	0.054

Panel C: Ideological Diversity and Abnormal Intraday Return Volatility Following Polarizing Boycotts

VARIABLES	**Pred. Sign**	(1) *AbIVola(0,+1)*	(2) *AbIVola(0,+3)*	(3) *AbIVola(0,+7)*
IdeoDiversityScore	(+)	0.046	0.045*	0.024
		(1.04)	(1.56)	(1.27)
Controls		YES	YES	YES
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adjusted R-squared		0.047	0.032	0.056

Notes: This table presents the regression results of testing Hypothesis 2. Panel A presents the regression results where the dependent variable is abnormal shares turnover, Panel B presents the regression results where the dependent variable is abnormal daily return volatility, and Panel C presents the regression results where the dependent variable is abnormal intraday return volatility. See Appendix B for detailed variable definitions. Continuous variables are winsorized at the 1st and 99th percentiles. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, in a one-tailed test if a directional prediction is specified, and two-tailed test otherwise.

Table 9: Additional Tests

Panel A: Redefining Nonpartisan Posters as Those with Relative Following Differences Below 0.3

VARIABLES	**Pred. Sign**	(1) Full Sample	(2) Posts with ≤5 cashtags only	(3) Posts with ≤5 cashtags & posters with above-median investment experience only	(4) Posts with ≤5 cashtags & posters who self-describe as traders only
Aligned	(-)	-0.094***	-0.104**	-0.081***	-0.112***
		(-3.014)	(-2.624)	(-3.397)	(-4.424)
Opposed	(+)	-0.004	-0.008	0.008	-0.010
		(-0.154)	(-0.276)	(0.385)	(-0.482)
Controls		YES	YES	YES	YES
Boycott FE		YES	YES	YES	YES
Clustering		By firm and by poster	By firm and by poster	By firm and by poster	By firm and by poster
Observations		77,190	62,003	27,376	17,098
Adjusted R-squared		0.172	0.180	0.113	0.125

Panel B: Ideology-Driven Social Media Opinions and Retail Order Imbalance Following Polarizing Boycotts

VARIABLES	**Pred. Sign**	(1) *AbROIBVol(0,+1)*	(2) *AbROIBVol(0,+3)*	(3) *AbROIBVol(0,+7)*	(4) *AbROIBTrd(0,+1)*	(5) *AbROIBTrd(0,+3)*	(6) *AbROIBTrd(0,+7)*
PctPosterAligned	(-)	-0.060	-0.080*	-0.060**	-0.069	-0.047	-0.033
		(-1.17)	(-1.63)	(-1.73)	(-1.22)	(-0.99)	(-0.73)
Controls		YES	YES	YES	YES	YES	YES
Day of week FE		YES	YES	YES	YES	YES	YES
Year FE		YES	YES	YES	YES	YES	YES
Clustering		By firm	By firm	By firm	By firm	By firm	By firm
Observations		125	125	125	125	125	125
Adj. R-squared		0.109	0.011	-0.066	0.062	-0.028	-0.043

Table 9 (Continued)

Panel C: Ideological Diversity and Retail Investor Disagreement Following Polarizing Boycotts

VARIABLES	Pred. Sign	(1) *AbRetailTurn(0,+1)*	(2) *AbRetailTurn(0,+3)*	(3) *AbRetailTurn(0,+7)*
IdeoDiversityScore	(+)	-0.000	-0.000	0.000
		(-0.24)	(-0.10)	(0.66)
Controls		YES	YES	YES
Day of week FE		YES	YES	YES
Year FE		YES	YES	YES
Clustering		By firm	By firm	By firm
Observations		125	125	125
Adjusted R-squared		0.400	0.117	0.048

Panel D: Post-Boycott Returns by Firm Response to Boycotts

	Firm response - explanation (n=41)	Firm response - policy reversal (n=19)	Firm response - double down (n=14)
BHAR(0, +3)	-1.41%**	-0.92%	0.15%
BHAR(0, +7)	-1.91%*	-1.36%	0.73%
	Firm response - silence (n=51)	Firm response - silence (n=51)	Firm response - silence (n=51)
BHAR(0, +3)	-0.01%	-0.01%	-0.01%
BHAR(0, +7)	-0.48%	-0.48%	-0.48%
	Diff (explanation - silence)	Diff (reversal - silence)	Diff (double down - silence)
BHAR(0, +3)	-1.40%	-0.91%	0.16%
BHAR(0, +7)	-1.43%	-0.88%	1.21%

Notes: This table presents additional analyses. Panel A repeats the test in Table 4, Panel A with an alternative definition of nonpartisans (those with relative following differences below 0.3). Panel B tests H1 with abnormal retail order imbalance as the dependent variable. Control variables are the same as those in Tables 6. Panel C tests H2 with abnormal retail shares turnover as the dependent variable. Control variables are the same as those in Tables 8. See Appendix B for detailed variable definitions. Continuous variables are winsorized at the 1st and 99th percentiles. Panel D presents univariate test of whether post-boycott returns depend on firm responses to polarizing boycotts. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, in a one-tailed test if a directional prediction is specified and two-tailed test otherwise.

Internet Appendix to:

Ideology-Driven Investment Opinions on Social Media and Responses to Polarizing Boycotts

Appendix IA1: Methodology of Identifying Boycotts of Public Companies from Trending Topics

This appendix documents the procedure used to identify boycotts of publicly traded companies that trended on X from April 2016 to October 2022. The overarching goal is to discover all trending topics that explicitly refer to a boycott of any publicly traded company. The classification proceeds in three steps.

1. **Data Collection.** I begin by scraping a total of 122,097 trending topics from Trend Calendar (https://us.trend-calendar.com/), a website that archives daily trending topics on X and Google. Each archived topic is clickable (e.g., Celtics) and links to posts that contained the topic on the date it trended. The dataset spans from April 2016 through October 2022.
2. **Keyword-Based Filtering (Step 1).** As a first pass, I search all 122,097 trending topics using the terms "boycott," "delete," "cancel," and "walkaway," which are selected to capture the most common language used to call for boycotts or "cancellations." This initial filter yields 51 trending topics that explicitly referred to boycotts or calls to cancel a product or company.
3. **Company Name Fuzzy Matching (Step 2).** Next, I identify 652 unique companies that were constituents of the S&P 500 index at any point during the 2016–2022 period from CRSP. I standardize each company's name by removing organization-type suffixes (e.g., "Corporation," "Corp," "Inc.," "Ltd.") to facilitate matching. Using the Python package *FuzzyWuzzy*, I then attempt to match these firm names with all remaining 122,046 trending topics (i.e., those not flagged by the initial keyword-based filter). This fuzzy matching algorithm identifies 16,516 trending topics as possible references to S&P 500 companies. However, most of these matches are invalid. For example, "space force," which trended on September 21, 2021, is incorrectly matched to "Extra Space Storage Inc." I manually review all 16,516 topics to determine which

are true positives and which are false positives, ultimately identifying 144 valid boycott-related topics.

4. **Manual Checking for Missed Companies/Brands (Step 3).** Finally, to capture any publicly traded companies or their subsidiaries, brands, or products that were not picked up in the first two steps, I examine the remaining 105,530 trending topics that could plausibly contain company or brand names. In particular, I look for references to major subsidiaries, brands, or product names that I have compiled during the initial steps. This targeted search identifies 62 additional valid boycott-related topics. Throughout this process, I keep a running checklist of known brand names and perform quick verifications (e.g., clicking on a trending topic to see all posts containing the topic) to confirm whether a trending topic refers to a publicly traded company.

By combining keyword searches, fuzzy matching, and focused manual browsing, I arrive at a dataset of 256 boycotts of publicly traded companies that trended on X from April 2016 to October 2022.

Appendix IA2: Methodology of Classifying Boycotts by Issue and Boycotter ideology

This table describes the methodology I employ to 1) classify social media boycotts into different categories and 2) determine the boycotter ideology for each boycott.

Polarizing issues:

Abortion: Women's access to abortion services and contraceptives.

A boycott is considered liberal if it protests a firm's policy to make abortion services or contraceptives less accessible. Example: July 17, 2022 trending topic "Walgreens".

A boycott is considered conservative if it protests a firm's policy to make abortion services or contraceptives more accessible. Example: September 4, 2021 trending topic "Lyft".

Climate change: Impact of industrial activities on climate change.

A boycott is considered liberal if it protests a firm's carbon-dioxide emissions. Example: October 5, 2020 trending topic "Exxon".

A boycott is considered conservative if it protests a firm's action to curb its carbon-dioxide emissions. There is no conservative boycott related to climate change in my sample.

COVID-19: Health risks of COVID-19; risks and benefits of COVID vaccines; necessity of mask mandates and vaccination mandates.

A boycott is considered liberal if it protests a firm's action to 1) downplay the health risks of COVID-19, 2) allow/amplify anti-vaccine voices, or 3) relax mask and vaccinate mandates for customers or employees. Example: January 19, 2022 trending topic "#BoycottStarbucks".

A boycott is considered conservative if it protests a firm's action to 1) warn about the health risks of COVID-19, 2) ban anti-vaccine voices, or 3) implement mask and vaccinate mandates on customers or employees. Example: January 25, 2022 trending topic "#BoycottWalmart".

Domestic/international politics: Corporate stances or policies on U.S. or international politics, including but not limited to corporate political donations, federal, state or local elections, immigration, freedom of speech, healthcare reform, Hong Kong protests, January 6 Capitol attack, murder of Jamal Khashoggi, and Russian invasion of Ukraine.

A boycott is considered liberal if it protests a firm's 1) support of Republican politicians, or 2) actions consistent with the Republican Party's policy platform. Example: October 7, 2022 trending topic "Home Depot".

A boycott is considered conservative if it protests a firm's 1) support of Democratic politicians, or 2) actions consistent with the Democratic Party's policy platform. Example: January 30, 2017 trending topic "#BoycottStarbucks".

LGBTQ+ rights: Accommodation for gender identity expression; depiction of LGBTQ+ persons in the media.

A boycott is considered liberal if it protests a firm's policy that 1) discourages gender identity expression or 2) negatively depicts LGBTQ+ persons. Example: October 20, 2021 trending topic "#NetflixWalkout".

A boycott is considered conservative if it protests a firm's policy that 1) accommodates for gender identity expression or 2) positively depicts LGBTQ+ persons. Example: February 25, 2021 trending topic "Hasbro".

Gun policy: Corporate relationships with the National Rifle Association (NRA); corporate stances on gun control.

A boycott is considered liberal if it protests corporate partnerships with the NRA or a lack of corporate policies supporting gun control. Example: August 9, 2019 trending topic "#BoycottWalmart".

A boycott is considered conservative if it protests corporations' severing ties with the NRA or corporate policies in favor of gun control. Example: February 24, 2018 trending topic "Delta and United".

Racial equality/policing policy: Corporate actions to address racial inequality; corporate behaviors towards customers and employees of color; corporate stances on the Black Lives Matter movement (BLM); corporate attitude toward law enforcement.

A boycott is liberal if it 1) demands that the firm do more to address racial inequality; 2) protests actual or perceived racial discrimination of customers and employees of color; 3) demands that the firm support BLM; or 4) condemns a firm's support of law enforcement. Example: April 4, 2017 trending topic "Pepsi".

A boycott is conservative if it 1) criticizes a firm's progressive policies to address racial inequality; 2) condemns a firm's support of BLM; or 3) condemns a firm's actual or perceived hostility towards law enforcement. Example: March 23, 2022 trending topic "Home Depot".

Non-polarizing issues:

Business events: Business decisions unrelated to the above polarizing issues, such as personnel hiring/departures, launches/cancellations of products/services, product recalls, price increases, etc.

Corporate misconduct: Illegal or questionable business practices and their related lawsuits/regulatory actions.

Employee rights: Employees' rights to form unions, earn fair wages, and work in a safe environment.

Gender equality Actions or policies that could be construed as biased against women.

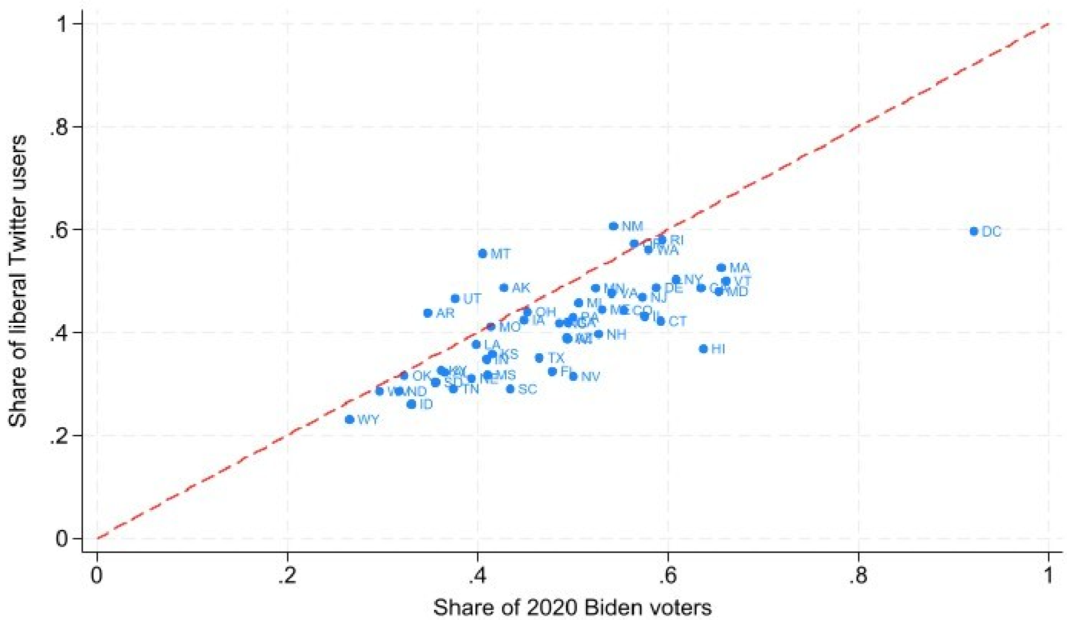
Popular culture controversy: TV shows and other types of media products that are controversial for reasons other than the polarizing issues mentioned above.

Poster privacy/data breach: Actions or policies that directly or indirectly lead to breaches of poster privacy.

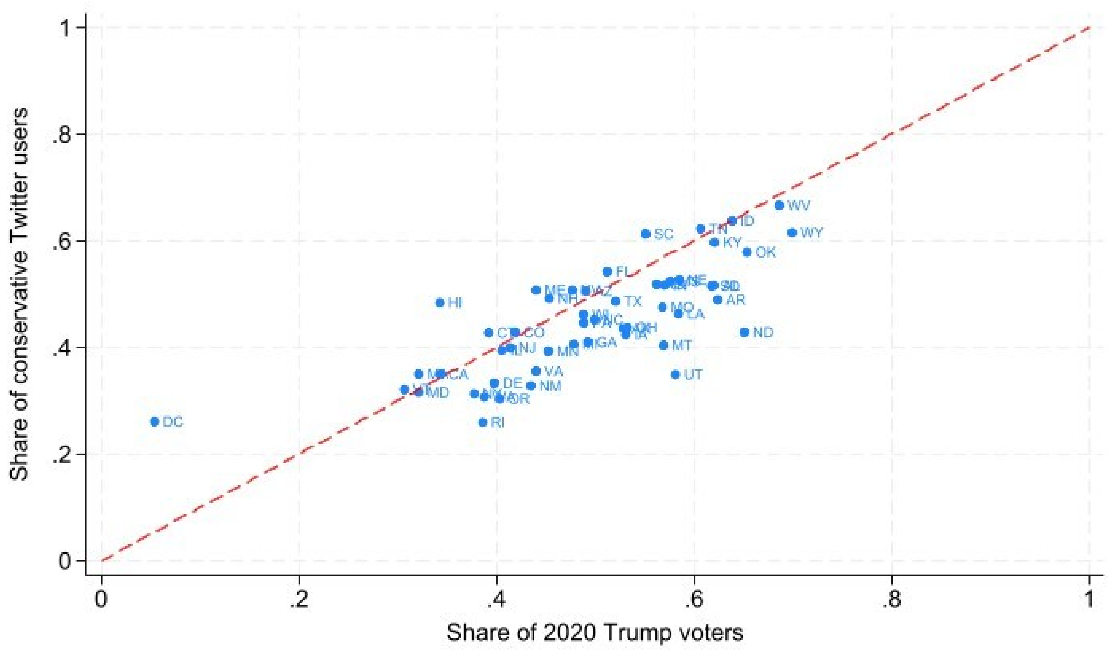
Product safety/customer experience: Product safety incidents; negative customer experiences with products/services.

Rumors: Various unsubstantiated rumors or conspiracy theories that do not pertain to the polarizing issues mentioned above.

Figure IA1: Share of Biden/Trump Voters and Liberal/Conservative Posters
Panel A: Share of 2020 Biden Voters and Liberal Posters by State

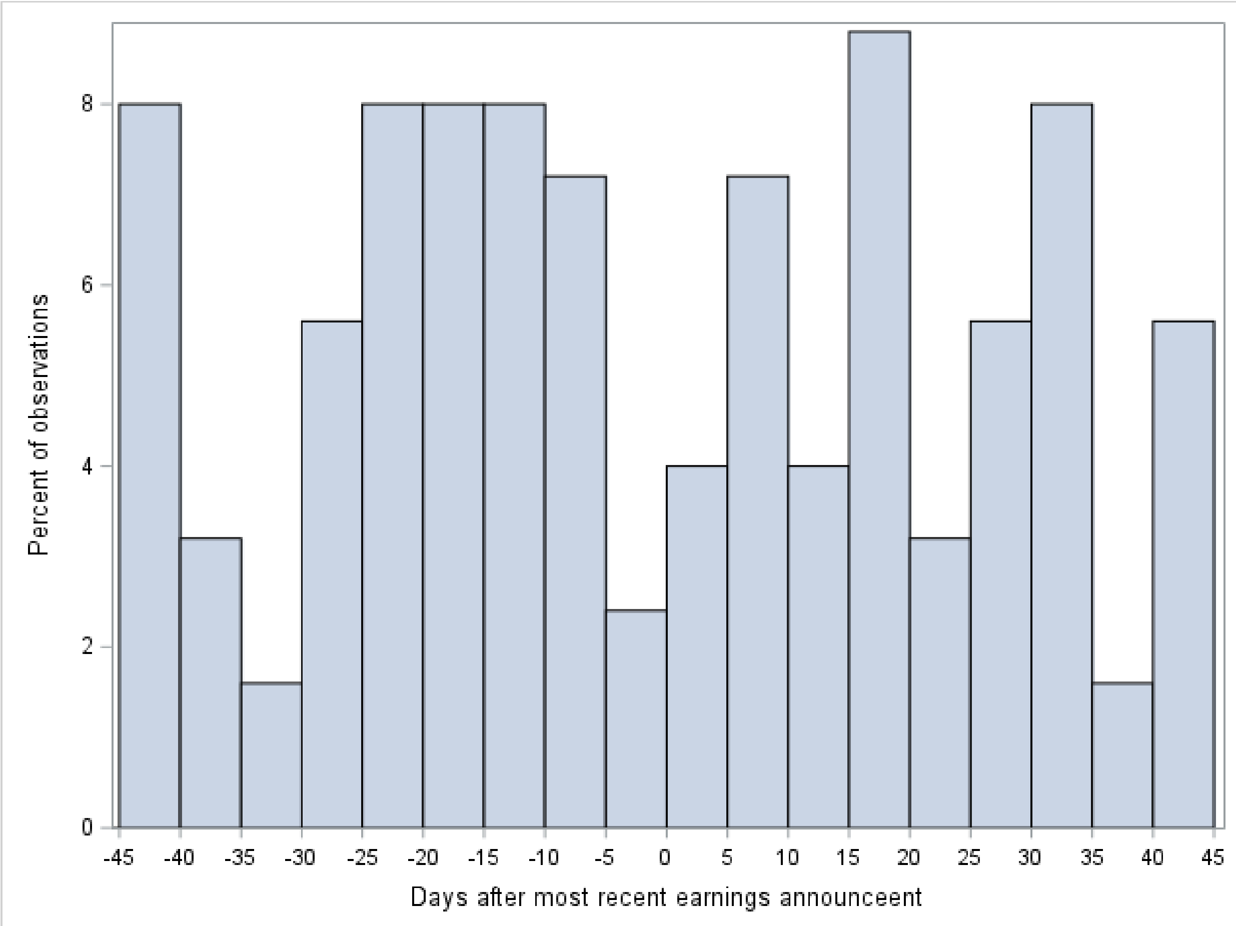


Panel B: Share of 2020 Trump Voters and Conservative Posters by State



Notes: The figure shows, by state, the relationship between the share of X posters classified as liberals (conservatives), according to the partisan accounts they follow, and the share of Biden (Trump) voters in the 2020 U.S. presidential election. Presidential election results by state are obtained from https://www.presidency.ucsb.edu/statistics/elections/2020. The red dotted line marks the 45-degree line.

Figure IA2: Boycott Trending Dates Relative to Earnings Announcements



Notes: This figure shows the distribution of boycott trending dates relative to the closest earnings announcement date. Following Mkrtchyan et al. (2023), I set any number of days less (greater) than -45 (45) to -45 (45).

Table IA1: Most Common Words in the Profiles or Posts of X Users in the Sample

Panel A: Top 15 Most Common Words in User Profiles

Most common words in poster profiles	Frequency
advice	1,696
stocks	1,138
options	984
crypto	931
opinions	831
conservative	648
investing	614
retired	585
former	543
markets	507
enthusiast	476
alerts	362
analyst	351
dms	314
endorsement	274

Panel B: Top 15 Most Common Words in Posts with Cashtags vs. Posts with Boycott Hashtags

Most common words in posts with boycotted firm cashtags	Most common words in posts with boycott hashtags
tsla (10,304)	never (200,780)
spy (5,942)	transmission (186,503)
stocks (5,108)	COVID (181,028)
earnings (4,479)	get (180,731)
CEO (4,462)	vaccine (175,916)

stock (4,187)	people (167,891)
nvda (4,071)	like (133,383)
amd (3,887)	tested (129,040)
ba (3,873)	admits (119,828)
short (3,850)	would (114,344)
qqq (3,645)	company (108,221)
week (3,583)	one (101,251)
company (3,483)	stop (99,947)
new (3,352)	ad (99,149)
users (3,336)	CEO (94,258)

Notes: This table shows the most common words in the profiles or posts of X posters in the sample. Panel A shows the most common 15 words in the profiles of X posters in the sample, as well as the word frequencies. Panel B shows the most common 15 words in the sample posts (i.e., posts containing cashtags, excluding the boycotted firms' own cashtags) and contrast them with the most common 15 words in posts containing boycott hashtags (excluding the boycott hashtags themselves) posted during the same time period. Word frequencies are in parentheses. Note that I was only able to collect posts containing boycott-related hashtags for 93 (74%) of the boycotts in the sample before the Twitter Academic API was abruptly shut down in June 2023. However, there is no reason to believe the most frequent words in posts about these boycotts are not representative of the overall sample.

Table IA2: Performances of Sentiment Classifiers for a Random Sample of 500 Posts

Panel A: Performance Metrics of Sentiment Classifiers

	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
GPT-4	76.00%	71.05%	73.22%	72.05%
Twitter RoBERTa	62.80%	57.26%	62.17%	58.70%
LM dictionary	55.00%	42.82%	41.63%	41.98%
FinBERT	24.00%	25.77%	31.64%	16.52%

Panel B: Performance Metrics of Sentiment Classifiers by Post Sentiment

	Positive Posts (80)			Neutral Posts (313)			Negative Posts (107)		
	Precision (%)	Recall (%)	F1 score (%)	Precision (%)	Recall (%)	F1 score (%)	Precision (%)	Recall (%)	F1 score (%)
GPT-4	63.00%	70.00%	66.00%	83.00%	80.00%	81.00%	67.00%	70.00%	68.00%
Twitter RoBERTa	41.00%	61.00%	49.00%	78.00%	64.00%	70.00%	53.00%	62.00%	57.00%
LM dictionary	28.00%	20.00%	23.00%	66.00%	71.00%	68.00%	35.00%	34.00%	34.00%
FinBERT	0.00%	0.00%	0.00%	56.00%	9.00%	15.00%	21.00%	86.00%	34.00%

Notes: This table shows the performance of NLP algorithms on a random sample of 500 posts (80 positive, 313 neutral, 107 negative), independently labeled by a research assistant. Panel A reports Accuracy, Precision, Recall, and F1 scores. Accuracy represents correct classifications as a proportion of total classifications. Precision, Recall, and F1 score for each sentiment category are defined as follows: Precision is the proportion of correctly classified posts in that category relative to all posts classified into that category by the algorithm; Recall is the proportion of correctly classified posts in that category relative to all posts classified into that category by the research assistant; F1 score is their harmonic mean. Overall scores are the averages across sentiment categories. Panel B reports Accuracy, Precision, Recall, and F1 scores for each sentiment category.